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Assessing the Impact of Substituting Interaction Types: An Empirical Study of the Interaction Equivalency Theory

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ASSESSING THE IMPACT OF SUBSTITUTING INTERACTION TYPES: AN EMPIRICAL STUDY OF THE INTERACTION EQUIVALENCY THEORY

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ABSTRACT

ASSESSING THE IMPACT OF SUBSTITUTING INTERACTION TYPES: AN EMPIRICAL STUDY OF THE INTERACTION EQUIVALENCY THEORY

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Multimedia technologies allow instructional designers to transform interpersonal interactions into interactions between learners and content. These learner–content interactions are more scalable in online, asynchronous distance education (DE) than interactions between learners and the instructor or interactions among learners. Additionally, learners sometimes prefer interactions with course content over interactions with their peers and instructor. Studies on learner–learner and learner–instructor interaction provide insight into the preferences and perceived effects of interaction types. However, the literature has not directly discussed the impact on performance resulting from substituting learner–content interaction for learner–learner interaction. This study examined the impact of substituting interaction types on perception of workload, perception of learning, and performance in an online, asynchronous, undergraduate-level setting of formal DE.

The results of this study showed (a) learner–learner interactions were perceived to be significantly more work than learner–content interactions, (b) learner–content interactions were perceived to be significantly more helpful in learning the material, (c) there was no significant difference in performance between the two interaction types, (d) interaction type did not significantly moderate the relationship between perception of workload and performance, and (e) interaction type did significantly moderate the relationship between perception of learning and performance.

DEDICATION

This dissertation is dedicated to my wife and best friend, Debbie, whom, for more than 30 years, has steadfastly supported my intellectual pursuits; to my parents, Robert and Ann, for instilling in me the value of seeing things through and equipping me intellectually and emotionally to persevere; and to my sisters, Sheryl and Carla, for always cheering me along in my adventures, Quixotic or otherwise.

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CHAPTER ONE

INTRODUCTION AND LITERATURE REVIEW

The primary aim of this study was to compare the performance of students who engaged in learner–content interactions to the performance of students who engaged in learner–learner interactions when those interaction types are mutually exclusive in otherwise-identical versions of the same instructional episode of an online, asynchronous course. This study sought to determine whether learner–content interaction can substitute for learner–learner interaction with no significant impact on learner performance. Secondarily, this study explored the impact of interaction types on students' perception of workload and perception of learning, and whether student performance was significantly related to the interaction type in an online, asynchronous, undergraduate-level setting of formal distance education (DE).

Studies comparing in-person and DE courses have commonly found performance differences but have not adequately explained the reasons for those gaps (Shearer et al., 2020). The confounding influences of environmental factors, temporal issues, learner characteristics, and media variables have frustrated comparative research since the days of educational television (Feldon et al., 2022; Means et al., 2010; Saba, 2003). These confounds, coupled with a lack of detail related to comparable activities, make it difficult to attribute performance differences to modality alone (Bernard et al., 2009; Feldon et al., 2022; Holmberg, 1995; Welch et al., 2022). Thus, rather than compare performance differences by analogizing student modality experiences, this study compared competency-referenced performance between identically situated DE learners.

Affordances and Barriers in DE

One benefit of DE is its potential to increase opportunities for people to pursue their educational goals (Dinmore, 2019). Learners often continue their education in a DE format because it suits their preference (Bernard et al., 2009; Cabral, 2016; Lei & Gupta, 2010; Padilla Rodriguez & Armellini, 2015; Pagano, 2021; Rhode, 2009). In other situations, the DE format allows learners to overcome barriers that make in-person education impracticable for them, such as time constraints, physical distance, or a disability (Daniel & Marquis, 1979; Fidalgo et al., 2020; Lei & Gupta, 2010; Mayfield-Johnson et al., 2014; Pagano, 2021). However, these opportunities can go unrealized when there are not enough resources to expand DE capacity and serve the diversity of unmet needs (Feldon et al., 2022; Shannon, 2019).

One factor that can affect DE capacity is budget constraint. Funding can limit technical infrastructure, stakeholder support, and the hiring and training of DE-proficient instructors. These funding limits often exist even after accounting for the cost of course design and development (Kasch et al., 2021; Lei & Gupta, 2010; Shannon, 2019). For instructors that are available, their instructional obligations and noninstructional duties, such as research and committee work, can reduce their capacity (Lei & Gupta, 2010; O'Doherty et al., 2018). Collectively, these constraints can limit DE instructors' ability to address and moderate interactions among learners, as well as their ability to address interactions between learners and themselves (Daniel & Marquis, 1979; Pagano, 2021). Whether due to infrastructure, support, or instructor availability, this long-standing capacity problem (Garcia & Weiss, 2019) intensified when the COVID-19 pandemic forced millions of learners into a DE setting (Feldon et al., 2022; Garrett et al., 2023; Katsarou & Chatzipanagiotou, 2021; Welch et al., 2022).

A secondary impact of the pandemic was its exacerbation of preexisting enrollment declines at nearly every level and in every sector of education in the United States (Dee & Murphy, 2021; Kim, 2022; Pavlov & Katsamakas, 2020). These enrollment declines were often accompanied by a loss of funding caused by reduced state and local aid, as well as reduced tuition-based revenue (Kim, 2022). Because instructional labor is the cost most closely related to enrollment levels, budget reductions are likely to further aggravate the instructor shortage. Just as state legislatures were slow to restore education budget cuts from the Great Recession of 2007–2008, there is no assurance that post pandemic education budgets will recover quickly (Gándara et al., 2023; Garrett et al., 2023; Jackson et al., 2021). Therefore, it is reasonable to expect the cascade of constraints—both those existing prior to and those resulting from the pandemic—to persist and compound the instructor capacity problem. Accordingly, there is a need for evidence-based instructional practices that will extend instructor capacity without compromising learners' performance (Anderson, 2003b; Feldon et al., 2022; Garrett et al., 2023; Kim, 2022).

When it is pedagogically and contextually appropriate for the audience and subject matter, one strategy that may help meet this challenge is to substitute learner–content interactions for learner–learner interactions in DE classes (Feldon et al., 2022; Kasch et al., 2021). Doing so may allow instructors to devote more time to learner–instructor interactions that provide the counsel, motivation, self-confidence, and relationship building that increases student performance (Kim, 2022; Qaqish et al., 2020; Winterer et al., 2020).

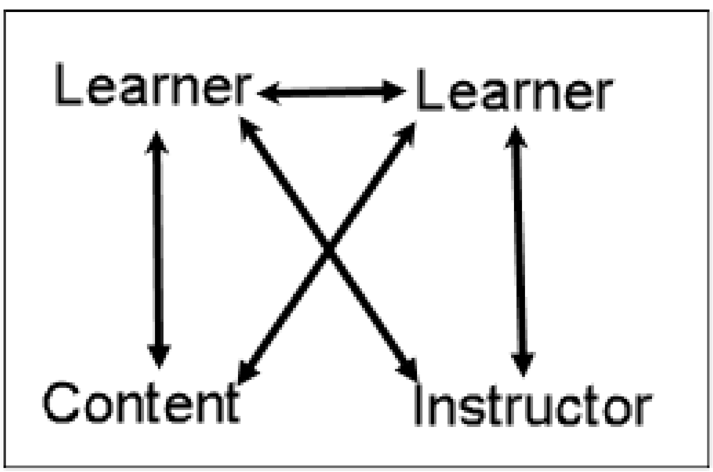
Literature Review

Since the earliest days of formal DE, instructional designers and educators have sought to duplicate the perceived effects of interactions that occur in traditional, in-person instruction

(Anderson & Garrison, 1998; Daniel & Marquis, 1979). As DE moved online in different formats and settings, Moore (1989) argued the imprecise and generic use of the term *interaction* hindered not only the scholarly discourse, but also the meaningful incorporation of interactions into the practice of formal DE. To move the study of interaction in DE toward a more structured dialogue supporting actionable research, Moore (1989) defined three types of interaction, as illustrated in Figure 1: (a) learner–content, (b) learner–learner, and (c) learner–instructor. Moore's framework remains the dominant construct for studying interaction types in DE (Alqurashi, 2019; Zimmerman, 2012).

Figure 1

Types of Interaction



Note. Adapted from "Editorial: Three Types of Interaction," M. G. Moore, 1989, *American Journal of Distance Education*, *3*, 1–7. https://doi.org/10.1080/08923648909526659

The relationships and interactions between learners and instructors depend on the instructional setting. But regardless of setting, the human embodiment of learners and the instructor is self-evident. Content, however, can manifest and be represented in multiple forms (Riffe et al., 2019).

Reduced to its essence for learner–content interaction, *content* is any textual, verbal, or image-based symbol that communicates meaning, regardless of media or medium (Riffe et al., 2019). The relevance of content depends upon its context and the purpose it serves in being communicated (Riffe et al., 2019). In Moore's (1989) schema, learner–content interaction serves to guide learners through an internal didactic conversation (Holmberg, 1995). During this self-dialogue, learners engage with the content to elaborate, select, segment, and rehearse the information encountered (Alqurashi, 2019; Rothkopf, 1996). By doing so, learners can receive feedback and confirmation, construct meaning, and achieve understanding (Aravind & Refugio, 2019; Graham & Massyn, 2019; Holmberg, 1995; Rothkopf, 1996; Wagner, 1997). For this study, relevant content was the textual and verbal material communicated in the context of the asynchronous, online course for the purpose of instructing learners in the subject matter, as bounded by the instructional objectives.

Although Moore (1989) provided a framework for studying interactions in DE, there remained a need for a functional definition of interaction (Feldon et al., 2022). One of the earliest and most enduring definitions described interaction in DE as an event involving two or more agents. Those agents are the whom or what involved in the interaction, such as the instructor, the learner, or the content (Wagner, 1994, 1997); agents must mutually influence one another via the reciprocal exchange of signals (E. Wagner, personal communication, August 23, 2020).

Early interaction research identified reciprocity as a core characteristic of interaction, noting that "watching/listening to broadcasts [or audio-visual material]" (Daniel & Marquis, 1979, p. 30) and other solitary activities lacking an exchange did not constitute interaction.

Consistent with this early view, Wagner’s reciprocal element made explicit the need for symmetry in learner–content, learner–learner, and learner–instructor interactions (Holden et al., 2010). More importantly, Wagner (1994, 1997) articulated the observable mechanics that constitute an interaction and distinguished those mechanics from an interaction’s purpose (e.g., to foster a sense of community) or result (e.g., students achieved higher scores on formative assessments). Wagner’s (1994, 1997) work has remained one of the most cited functional definitions in interaction literature (Bernard et al., 2009; Gray, 2019; Miyazoe & Anderson, 2010; Xiao, 2017). For this study, interaction was defined as the mutual influencing of content and learners through the reciprocal exchange of signals.

The Role of Interaction

Dewey (1916) asserted learners’ interactions with objects and their interactions with people are inseparable in producing meaning from those interactions. Dewey’s view reflects the didactic and dialectic or Socratic methods of face-to-face interaction that dominated formal education of that era. These methods originated in educational environments as far back as Plato, where presentation of content was bounded by learners’ physically- and time-restricted proximity to the instructor (Anderson, 2003b). It was the instructor who spoke, scribed, or otherwise presented content through mediums of the time while interacting with the learners. The perceived absence of these instructor- and learner-based interactions was an early criticism of DE and has remained a commonly expressed concern (Bozkurt et al., 2020; Saba, 2003).

Vygotsky (1978) and other social constructivists argued all three types of interaction are always necessary and equally important in DE. The influence of social constructivism, including the impact of facilitating interaction, communication, and collaboration, was a dominant theme in DE research from 1980–2014 (Zawacki-Richter & Naidu, 2016). More recently, Mehall

(2020) argued for the importance of a social constructivist dynamic in DE. The suggested benefits of such designs include students' perception of increased performance along with higher levels of student and faculty satisfaction (Mehall, 2020). However, early in the debate, Daniel and Marquis (1979) noted the conflicts that arise when pedagogical preferences related to interaction are at odds with learners' reasons for choosing DE in the first place. Likewise, as Anderson (2003a) opined, learner–learner interaction may be central to constructivist learning theories, but it is less critical to cognitive and behaviorist approaches. In an examination of these social construct arguments, Drouin (2008) elaborated on sense of community and satisfaction as they relate to evidence of achievement and retention. Drouin found (a) learner–instructor interactions in online courses are not significantly related to a sense of community, (b) some online students specifically choose that modality because it does not promote community, and (c) a community dynamic is neither essential for, nor significantly related to, retention or measured performance in an online course. Similarly, Murphy and Fortner (2014) found instructor participation in online discussion yielded the same quality of student contributions as when there was no instructor participation, but instructor participation correlated to a decrease in student participation.

Anderson's Interaction Equivalency Theory

This study's theoretical foundation was rooted in Anderson's (2003a) interaction equivalency theory in DE, which is comprised of two distinct theses. The first thesis posits an equivalent effect on learning from substituting interaction types. The second thesis suggests an additive effect when increasing the quantity of any interaction type. Because the literature has paraphrased Anderson's theory differently, it is important to present it as originally stated:

> Deep and meaningful formal learning is supported as long as one of the three forms of interaction (student–teacher; student–student; student–content) is at a high level. The other two may be offered at minimal levels, or even *eliminated* [emphasis added], without degrading the educational experience.
> High levels of *more than one* [emphasis added] of these three modes will likely provide a more satisfying educational experience, though these experiences may not be as cost or time effective as less interactive learning sequences. (Anderson, 2003a, p. 4)

At its core, Anderson's (2003a) interaction equivalency theory expresses the relationship between intentionally designed interactions and the learning that results from those interactions in the context of formal DE.

Anderson (2003a) discussed deep and meaningful learning relative to defined learning objectives, the instructional setting (e.g., classroom-based, online), and learner audience (e.g., working professionals or college students). Miyazoe and Anderson (2010) referred to this as the quality of the educational experience. In summarizing multiple studies that examined generative learning strategies, Mayer (2021) framed deep and meaningful learning relative to performance. Thus, if learner performance reflects deep, meaningful learning, the logical criteria for measurement are the instructional competencies, or objectives, used to orient the learners (Cavalier & Klein, 1998; Gray, 2019; Klein & Pridemore, 1994; Mager, 1997; Wagner, 1997; Zimmerman, 2012).

Although deep and meaningful learning is measured relative to competency-referenced performance, the level of interaction is measured by the quantity of learner–content, learner–learner, and learner–instructor exchanges (Anderson, 2003a; Moore, 1989). In Wagner's (1997) agent-centric terms, the quantity of interactions impacts the workload imposed on the student-agent. The rationale for this interaction metric is when there are more interactions (i.e., a higher workload) involving learners, their engagement is required. More specifically, learners are required to be attentive, stay involved, and complete the task (Fulgham et al., 2009).

Perceptions and Performance

The distinction between learners' perceptions and measured performance is important to note when discussing Anderson's (2003a) theory. Literature to date has primarily examined learners' perception of performance, as well as their preference for, and satisfaction with, increased learner–learner and learner–instructor interaction (Bernard et al., 2009; Katsarou & Chatzipanagiotou, 2021; Zawacki-Richter & Naidu, 2016).

Student Perception of Learning

Rhode (2009) found subjects reported learner–learner interaction as the least important element of the DE course. Research by Cabral (2016) and Miyazoe and Anderson (2010) showed learners preferred, or ranked as more important, their interaction with content above that of interaction with instructors and other learners in an online setting. Niemann (2017) found similar preferences in a study examining priorities for developing scalable components in DE, and Kasch et al. (2017) reached the same conclusion when it came to the scalability of interaction types.

Alqurashi (2019) and Kuo et al. (2014) both specifically examined interaction types as predictors of learner satisfaction in combination with other independent variables. In both studies, learner–content interaction was the strongest and most significant predictor of satisfaction; learner–instructor interaction was the weakest. Similarly, a critical review of DE interaction literature from 2010–2019 found learner–content interaction correlated to learner satisfaction and course completion whereas learner–learner interaction did not (Katsarou & Chatzipanagiotou, 2021).

Student Perception of Workload

Unlike the large number of studies examining perceptions of learning from specific types of interactions, there has been scant research on learners' perception of the workload associated with specific interaction types (i.e., learner–content, learner–learner, or learner–instructor). There is, however, a substantial body of literature examining perceptions of overall workload in different DE settings. That corpus of research was instructive in framing this study's inquiry related to interaction types.

Valenta et al. (2001) conducted a content analysis of the DE literature from 1985–2000 to identify student attitudes toward technology-mediated learning, finding students consistently reported online classes as imposing an increased workload. In looking at specific elements of online classes, Smart and Cappel (2006) examined student perceptions of two online learning units that included discussion questions and optional audio clips. When asked whether the time and effort needed to complete the units was worth what they gained, the subjects largely reported it was not. Similarly, Smidt et al. (2014) examined student perceptions of an online course using learner–learner interaction through discussion questions. Students reported workload as one of the more negative aspects of the course, describing discussion boards as "busywork" (Smidt et al., 2014, p. 51) that stifled creativity with closed-end, overly structured prompts. In a related line of inquiry, Razami and Ibrahim (2021) surveyed 377 university students about their experience with online education; more than half reported they had difficulty interacting with their instructor and classmates. More recently, Beena and Sony (2022) reported a mean of 12.95 on a scale of 1–20 for 322 online undergraduate students' responses to "How hard did you have to work to accomplish your level of performance in your online learning during Covid-19?" (p. 7); performance was framed as the students' perception of having accomplished various tasks in the course. When asked in the negative how unsuccessful they were in accomplishing those tasks, the mean response was 12.30 on a scale of 1–20 (Beena & Sony, 2022). Thus, the researchers concluded, students perceived they had to work hard but were not necessarily successful in translating that effort into accomplishing the course activities.

Research has consistently shown students perceive DE courses as imposing a higher workload (Smidt et al., 2014; Valenta et al. 2001). A major factor in shaping that perception is how course design dictates the way students interact with the content, the instructor, and each other to meet their perceived needs. Although multiple studies have echoed the perception of increased workload, in general, none have appeared to attempt correlating the perceived workload for a particular interaction type with deep and meaningful learning measured by competency-referenced performance. Rather, the correlations reported, if any, have been between perceived workload for a particular course or DE in general, and simply completing the course. Still, the consistency of the findings in available studies does provide insight to student attitudes about workload in DE courses at a macro level. This insight, if coupled with empirical data on the measured performance associated with different interaction types, may inform choices about the appropriate mix of interaction types in DE courses (Beer, 2019; Daniel & Marquis, 1979).

Impact on Performance

Bernard et al. (2009) conducted a meta-analysis of 74 studies between 1985–2006. That analysis focused on Anderson's (2003a) second thesis, which posits the additive effect of interaction types in formal DE courses. All three interaction types were present in each of the studies; the researchers found the additive effect from increasing learners' workload for one interaction type in the presence of the other types tended to improve outcomes and attitudes. Padilla Rodriguez and Armellini (2015) studied results from three different DE courses in a corporate training environment. In the study, an existing online course was redesigned into three different courses. Each course included all three types of interaction. In each course, one interaction type presented a high workload and the other two had a low workload. The researchers concluded the three courses were equally effective in meeting what has become Kirkpatrick and Kirkpatrick's (2016) Level 4 return on organizational expectations. At the same time, only 9 of 46 respondents to the end-of-course evaluation for the learner–learner version of the course rated learner–learner interaction as the most enjoyable aspect of the course (Padilla Rodriguez & Armellini, 2015). As Xiao (2017) observed, however, neither Bernard et al. nor Padilla Rodriguez and Armellini substituted interaction types or indicated the independence of one interaction type from the others.

Graham and Massyn (2019) conducted a systematic review of research from 2007–2018 on Anderson's (2003a) equivalency theory. Of the 25 studies examined, only one was classified as having addressed Anderson's first thesis related to substitutivity. In that one study, Markewitz (2007) created two online learning modules in a continuing education program for laboratory professionals; one had integrated learner–learner interaction and the other had no opportunity for learner–learner interaction. Both modules had the opportunity for learner–instructor and learner–content interaction but otherwise were functionally identical. Notwithstanding the categorization by Graham and Massyn, Markewitz did not test the substitutivity of interaction types. As Markewitz (2007) described the study, the question investigated was whether there was "a significant difference in test scores between a class that experiences student–student interactions in their course and a class who does not" (p. 8). Hence, Markewitz added learner–learner interaction to the other two interaction types in one of the modules. By doing so, the test was *de facto* of the additive effect of Anderson's second thesis, not the substitutive effect of the first thesis.

Mehall (2020) also suggested additional interpersonal interaction (i.e., learner–learner and learner–instructor) leads to improved academic performance. Although academic performance in DE courses may correlate with interpersonal interaction, Long et al. (2011), to whom Mehall (2020) pointed, based their finding of improved performance on a correlation to the workload imposed by learner–learner interaction. That is, students in online courses with more learner–learner interactions performed better than those in courses with fewer learner–learner interactions. Here, again, the study measured an additive effect of the same type of interaction, as contemplated by Anderson's (2003a) second thesis. Left unexplored was what factors, either intrinsic to students or structurally to the 432 courses reviewed, might also explain the performance difference.

Likewise, Munabi et al. (2020) compared performance differences on summative assessments between those that participated in a learner–content intervention in addition to their face-to-face course and those that did not. Thus, as with Long et al.'s (2011) study, Munabi et al. did not examine substitutivity. Similarly, in their study of bachelor's and master's degree students, Dibra et al. (2021) explored the effect of different interaction types on 1,698 students taught by 26 different faculty at 12 universities in four different modalities. Students reported their perception of the interaction's effect on three conceptual dimensions of outcomes: learning, satisfaction, and quality. The study did not isolate the effects of the different interactions on the three types of outcomes and did not provide a measure of the learning (i.e., performance).

The extant research on interaction types reflects Persky et al.’s (2020) observations that many educational research projects have reported only participants’ perceptions, such as satisfaction and confidence, but have provided no measure of academic performance resulting from the intervention. Additionally, most studies related to educational interventions have involved subjects that are graduate students studying educational technology (Anderson, 2015; Maurino, 2007). Moreover, prior research has demonstrated learners, especially novice learners, are often unable to accurately gauge their own competence level (Dunning et al., 2003; Emory & Luo, 2020; Pennycook et al., 2017).

There are other potential limits to conclusions drawn from data that relies exclusively on self-reporting. Data based solely on self-reporting present challenges to internal validity, such as differential reactivity in the form of reporting bias. Reporting bias has been well-documented and occurs when subjects underrate, overrate, or misrate what they self-report (Stone et al., 2000). Hence, learners’ perceptions of their competence, performance, or the interaction type they prefer does not necessarily correlate with whether an interaction type impacts their measured performance on a competency-referenced assessment (Bernard et al., 2009).

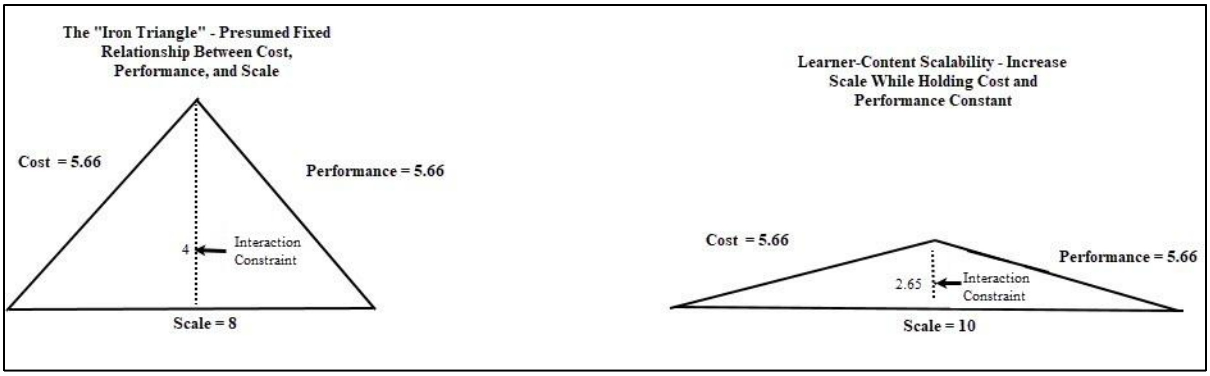
Purpose of the Study

The ability to achieve deep and meaningful learning through additional interaction, as posited in Anderson’s (2003a) second thesis, has been well-studied. Similarly, research to date supports the argument that social constructivist dynamics such as satisfaction, social interaction, and community building, can be desirable results of including learner–learner and learner–instructor interaction in DE courses (Chatterjee & Correia, 2020; Prupis, 2023; Shearer et al., 2020). However, there has been a pronounced dearth of scholarly inquiry into Anderson’s (2003a) first thesis—a deliberate course design can “substitute one type of interaction for the other” (p. 4) without significantly impacting performance. This study helped fill that gap by challenging “untested assumptions” (Anderson, 2003b, p. 141) and providing evidence that allows educators and instructional designers to “avoid mistakes and adjust practice [to be] compatible with the best available evidence [even if that evidence] is counter-intuitive” (Feldon et al., 2022, p. 25). By empirically testing the substitutivity of learner–content and learner–learner interaction in a sample of community college students not involved with educational technology, this study provided more diverse evidence of the impact from substituting interaction types. To that end, this study provided empirical evidence of the impact on competency-referenced, measured performance from substituting learner–content and learner–learner interaction in an online, asynchronous, undergraduate-level setting of formal DE.

When designs that substitute scalable interaction types are supported by empirical research, those designs can be used to increase capacity in pedagogically and contextually appropriate asynchronous, DE courses by reducing constraints associated with specific interaction types (Al Mamun et al., 2022; Bikowski et al., 2022). As illustrated in Figure 2, reducing the magnitude of interaction constraints such as cost, time, and complexity allows designers to manipulate the Iron Triangle of Education (Lane, 2014) by increasing class size (i.e., scale) without increasing delivery cost or decreasing learner performance (Kasch et al., 2017, 2021). Instructors in these courses can then reframe their role to better provide learners with the learner–instructor interactions shown to support learner motivation, self-confidence, and academic performance (Bernard et al., 2009; Kim, 2022; Qaqish et al., 2020; Winterer et al., 2020).

Figure 2

Manipulating the Iron Triangle of Education



Note. Adapted from "Placing Students at the Heart of the Iron Triangle and Interaction Equivalence Theorem Models," by A. Lane, 2014, *Journal of Interactive Media in Education*, *5*, 1–8. https://doi.org/10.5334/jime.ac

Research Questions

The methodology explained in Chapter 2 addressed the following research questions and associated hypotheses:

Research Question 1. Does interaction type impact students' perception of workload?

Hypothesis 1. There will be no significant difference in perception of workload between the learner–content interaction group and the learner–learner interaction group. This hypothesis is adapted from Kuo et al. (2014).

Research Question 2. Does interaction type impact students' perception of learning?

Hypothesis 2. There will be no significant difference in perception of learning between the learner–content interaction group and the learner–learner interaction group. This hypothesis is adapted from Kuo et al. (2014).

Research Question 3. Does interaction type impact performance?

Hypothesis 3. There will be no significant difference in performance between the learner–content interaction group and the learner–learner interaction group. This hypothesis is adapted from Anderson (2003a).

Research Question 4. Does interaction type moderate the relationship between students' perception of workload and performance?

Hypothesis 4. Interaction type will not significantly moderate the relationship between students' perception of workload and performance. This hypothesis is adapted from Anderson (2003a) and Kuo et al. (2014).

Research Question 5. Does interaction type moderate the relationship between students' perception of learning and performance?

Hypothesis 5. Interaction type will not significantly moderate the relationship between students' perception of learning and performance. This hypothesis is adapted from Anderson (2003a) and Kuo et al. (2014).

CHAPTER TWO

METHOD

Participants

Sixty-six students from a large, urban community college in the southwest United States participated in this study. Participants were those enrolled in courses related to their paralegal studies major and established academic readiness based on criteria that have equivalent course success levels for students entering the program (Hauert et al., 2021). The students self-enrolled in the courses based on their progress in the program during the Fall 2022 semester. Participants were at least 18 years old, provided with informed consent information, and allowed to opt-out of having their data used in the study. The informed consent document is included in Appendix A. Because the researcher also served as the instructor, informed consent was managed by an independent faculty member to avoid a conflict of interest.

Research Design

This study used an experimental design to measure the impact of interaction types on perception of workload, perception of learning, and measured performance in an online, asynchronous, undergraduate-level setting of formal distance education (DE). The learning episode for the study covered automobile insurance because it is commonly encountered by paralegals in their work. Randomized assignment to treatment groups was accomplished using the SPSS random sample function. Using this method, 50% of the students, or cases, were randomly assigned to the learner–learner group and 50% were randomly assigned to the learner–content group to test the equivalency hypotheses of the first three research questions.

An *a priori* power analysis estimated the minimum sample size required for two-tailed *t* tests (i.e., Research Question 1, Research Question 2, and Research Question 3) and multiple regression analyses (i.e., Research Question 4 and Research Question 5). The input parameters for the *t* tests were a medium effect size (d = .5), significance level of .05, and power level of 0.8. Input parameters for the multiple regression were a medium effect size (f^2 = 0.15), significance level of .05, and power level of 0.8. Three predictors of performance were used as the dependent variable: perception of workload/learning, interaction type, and a hypothesized moderating effect of the first two variables (i.e., perception x interaction type). The target sample size was 128 participants for the *t* tests and 77 participants for the regressions. The expected sample size was approximately 100 participants. The actual sample size was 66, yielding a power level of .52 for the *t* tests and a power level of .73 for the multiple regressions.

Operationalization of Interaction Types

Participants accessed material through the Canvas learning management system (LMS) used for DE courses at the institution. Camtasia was used to create narrated, PowerPoint-supported lectures. The learner–content group accessed an interactive version of the lecture but did not engage in learner–learner interaction. Members of the learner–learner group interacted with each other through the LMS discussion feature and viewed a version of the lecture with identical content but without the content’s interactive component. Table 1 summarizes the interactions for both treatment groups.

Table 1

Treatment Group Interactions

Element	Treatment group	
	Learner–content	Learner–learner
Content	Participants viewed an interactive version of a multimedia lecture containing adjunct questions with confirmatory or corrective feedback.	Participants viewed a *non*-interactive version (no adjunct questions) of the same multimedia lecture but containing mandatory check-in responses by participants.
Learner	Participants did not engage in learner–learner interaction and were not provided learner–learner opportunity in the LMS; participants in this treatment group were partitioned from, and not visible to, participants in the learner–learner group.	Participants engaged in learner–learner interaction using the discussion feature of the LMS; participants in this treatment group were partitioned from, and not visible to, participants in the learner–content group.
Instructor	Participants could interact with the instructor through an “Ask the instructor” discussion thread or through private message.	Participants could interact with the instructor through an “Ask the instructor” discussion thread or through private message.

The multimedia lecture was formatted using Clark and Mayer’s (2016) guidelines for organizational graphics. The lecture began with a presentation of learning objectives to serve as an orienting activity, which has been shown to correlate to higher performance and motivation (Cavalier & Klein, 1998; Klein & Pridemore, 1994). The multimedia lectures were hosted on Knowmia.com and included closed captions to make them accessible to any hearing-impaired students. Using features of the LMS, learners in the two treatment groups were partitioned from each other and could not see each other’s activities or interact across the boundaries of their assigned treatment group in the LMS.

Learner–Content Interaction Group

Moore (1989) described learner–content interaction as occurring when learners “talk to themselves” (p. 1) about the information encountered in a lecture. Moore analogized the earliest forms of interaction with a didactic text to the modern practice of interacting with computer software and video. Subsequently, Anderson (2015) reaffirmed the centrality of Moore (1989) and Wagner (1994) when exploring interaction. In doing so, Anderson emphasized the quarter-century of technological advances to media and online environments that afford learner–content interaction with different types of feedback.

To create the learner–content interaction for this study, adjunct questions with confirming and corrective feedback were inserted throughout the multimedia lecture (T. Anderson, personal communication, November 8, 2020; Campbell & Mayer, 2008; Garcia-Rodicio, 2015). When used as a self-testing generative activity, adjunct questions can increase learners' attention to, and retention of, the targeted material. Adjunct questions also facilitate cognitive processes leading to the construction of new knowledge while promoting deep and meaningful learning as measured by performance (Anderson & Biddle, 1975; Brod, 2020; Fiorella, 2022; Fiorella & Mayer, 2016; Grabowski, 2004; Hamaker, 1986; Kember, 1994; Mayer, 2021; Orimogune, 2012; Rothkopf, 1970). Quizzes included in multimedia learning episodes serve the same function as adjunct questions inserted into printed text (Fiorella, 2022; Garcia-Rodicio, 2015; Mayer, 2021; Valdez, 2013; van der Meij & Böckmann, 2021; Xie et al., 2019). Research has further shown self-testing in multimedia, especially low stakes quizzing, is most effective when used as corrective feedback and when the questions are interpolated between segments of the video to help learners maintain attention and improve learning (Enser & Enser, 2020; Fiorella, 2022). Knowmia allows quizzes to either force review of content following an incorrect response or to automatically move to the next media segment. Because students interacting with printed content would not be forced to reread a section, participants were not forced to repeat the content. Participants were not allowed to skip content but had the option of adjusting playback speed.

They could also return to any prior point of the presentation by dragging the playback indicator to that point.

Learner–Learner Interaction Group

The learner–learner group viewed a version of the multimedia lecture with identical content but without interactive questions. Instead, this group's lecture had periodic, mandatory check-ins requiring learners to acknowledge they were present and attending the lecture. For learner–learner interaction, the group engaged in the generative activity of self-explaining or elaboration and peer discussion (Fiorella & Mayer, 2022; Grabowski, 2004; Mayer, 2021).

Participants were provided prompts in the form of short vignettes that mirrored the stems of quiz questions from the learner–content group's interactive version of the lecture. These vignettes illustrated an application of concepts from the material covered in the lecture. The learner–learner participants then created their own vignette that also illustrated the principle and critiqued the vignette of one other participant. Moore (1989) explicitly recognized this type of peer discussion and feedback as learner–learner interaction that "acknowledges and encourages the development [of] expertise [and] also tests it" (p. 4). As well, Anderson (2015) acknowledged this type of peer-to-peer discussion as providing learner–learner interaction and as an appropriate substitute for the learner–content interactive videos in testing the substitutive prong of his interaction equivalency theory (T. Anderson, Personal communication, November 8, 2020). Using student-generated examples, or vignettes, to anchor discussion in online courses can be an effective instructional tool for developing higher order thinking and transferring knowledge (Jeffries & Maeder, 2006; Kish, 2006; Szedlak et al., 2019). When used to prompt elaboration, reorganization, and reconceptualization, vignettes serve as a generative learning activity (Grabowski, 1996; Kish, 2006; Wittrock, 1990).

Instruments

Participants completed surveys on their perception of workload and perception of learning for their respective interaction types. Both surveys used a 5-point Likert scale. For each respondent, their responses to the perception of workload and perception of learning surveys were averaged, respectively. The mean for both surveys for all respondents were calculated by interaction type to address Research Question 1 and Research Question 2. Participants also completed a 10-item, multiple selection summative assessment to address Research Question 3. Each question was worth 0–5 points, for a maximum score of 50 points. The mean performance score was calculated by interaction type to address Research Question 3.

Measurement of Perceptions of Workload and Learning

Participants completed a survey asking them to rank their perception of workload and their perception of learning for their assigned interaction type. The perception questions were framed to elicit a response that was informed by the participants' experience when engaging in the tasks required for their assigned interaction type. In this way, participants in the two groups not only reported on psychometrically equivalent constructs, but also reported on a common measure of workload and learning. The survey was adapted from Kuo et al.'s (2014) study that examined the correlation between interaction type and student satisfaction with the learning, as well as whether interaction type predicted student satisfaction with the learning. Kuo et al.'s (2014) survey was comprised of items related to perception of workload and perception of learning with established Cronbach alphas of .92 (learner–content) and .94 (learner–learner). Thus, it was an appropriate framework to adapt for this study.

Table 2 and Table 3 list the survey questions for perception of workload and perception of learning. A pilot for the perception of learning survey yielded a Cronbach alpha of .85. The pilot for the perception of workload survey yielded a Cronbach alpha of .79. Because the perception of workload survey consisted of two items, it was further examined using a Spearman coefficient, which yielded a Rho of .66 (significant at .287; $\alpha = .05$, $n = 34$). The survey instrument for the learner–content group is included in Appendix B. The survey instrument for the learner–learner group can be found in Appendix C.

Table 2

Perception of Workload Survey Questions

Learner–content	Learner–learner
1) Viewing the video lecture and attempting the questions that were part of the lecture was a lot of work. 2) Reading and thinking about the explanation displayed after each question was a lot of work.	1) Reading the question, considering the material, and then preparing and posting my own, original responses in the discussion group was a lot of work. 2) Reading the response from at least one of my classmates to the discussion question, considering that response, and then preparing and posting feedback to a classmate was a lot of work.

Table 3

Perception of Learning Survey Questions

Learner–content	Learner–learner
1) Viewing the video lecture and attempting the questions that were part of the lecture helped me understand the material. 2) Reading and thinking about the explanation displayed after each question helped me understand the material. 3) On the occasion(s) that I chose to replay parts of the lecture related to questions I missed or that I wanted to view again, it helped me understand the material. 4) Viewing the video lecture and doing the quiz questions built-in to the lecture helped me score higher on the quiz at the end of the week.	1) Reading the question, considering the material, and then preparing and posting my own, original responses in the discussion group helped me understand the material. 2) Reading the response from at least one of my classmates to the discussion question, considering that response, and then preparing and posting feedback to a classmate helped me understand the material. 3) On the occasion(s) that I chose to review feedback I received from my classmates about my posts in the discussion group, it helped me understand the material. 4) Participating in the discussion helped me score higher on the quiz at the end of the week.

Measurement of Performance

Performance was measured based on participants' summative assessment scores for the material covered in the instructional episode. The assessment for both groups consisted of selected response questions that tested participants' ability to transfer and apply the subject matter. Individual scores on the assessment ranged from 0–50. All questions were developed following evidence-based principles for designing effective selected-response questions (Atalmis, 2018; Haladyna, 2004, 2018; Haladyna et al., 2019). The assessment items were based on question structure and content common in the participants' law-related discipline. To establish content validity, the items were reviewed by subject matter experts and piloted with the same population of students during a semester prior to this study. The summative assessment for performance is provided in Appendix D.

Procedure

The module for this study was placed in the seventh week of a 12-week course. During the first 6 weeks, students in each treatment group engaged in activities identical to what they experienced during the study in Week 7: the learner–content group engaged with interactive multimedia, but not with each other and the learner–learner group engaged in peer discussion, but not with interactive multimedia. The pre-study period provided students time to orient to the course, ensure they had the necessary technology, and become familiar with how their assigned interaction activities operated. To further help students acclimate, and to minimize extraneous workload, the LMS course environment was identical in layout and structure to all the courses in the participants' program of study at the institution. Within that program, all courses, regardless of modality, used a common LMS course design with the learning objectives, activities, and material organized the same way every week. Thus, by the 7th week, students were more likely to be comfortable and familiar with the mechanics of the course and prepared to complete the instructional episode for this study.

Participants' demographic data were obtained from the institution's student information system. Evidence of participants' completing their assigned version of the multimedia lecture was downloaded from Knowmia. Evidence of students in the learner–learner treatment group completing the learner–learner interaction was downloaded from the LMS discussion area. Results of the perception of workload and perception of learning survey, as well as the results from the summative assessment used to measure performance, were downloaded from the LMS. The demographic data, summative assessment scores, and survey responses were then exported to a spreadsheet and associated with an ordinal record number for each participant.

Data Analysis

A spreadsheet of associated data was imported into SPSS and examined for accuracy and completeness prior to the analysis. Frequencies were checked for each variable to confirm that values were within their possible range. There were no missing data.

Demographic Equivalence Between Study Groups

Cross-tabulations were used to summarize the demographic characteristics of the students using frequency distributions classified by gender, age, and race/ethnicity divided into the two interaction groups. Demographic equivalence of the two interaction groups was assessed with Cramer's V to ensure any differences between their performance was due to interaction type and not differences in gender, age, and/or race/ethnicity (Marchant-Shapiro, 2020; Tabassum & Akhter, 2020). The value of Cramer's V, which can range from 0–1, should be less than 0.20, which indicates a weak relationship between the demographic factors of the participants and their assigned interaction type. A larger value would indicate the two groups of students were not demographically equivalent to each other (Agresti, 2018; Cognos Analytics, 2023).

Comparative Analysis

To address the hypotheses corresponding to the first three research questions, a series of two-tailed *t* tests determined whether there was an effect of interaction type on perception of workload, perception of learning, and performance, respectively. Independent samples *t* tests are appropriate when the research aim is to determine if differences exist between two groups on a continuous dependent variable (Field, 2017; Gamst et al., 2008). The independent variable was the interaction type. Learners' perception of workload, perception of learning, and performance were the dependent variables, one at a time in each *t* test.

The mean and standard deviation were computed for perception of workload, perception of learning, and performance. The null hypotheses, which proposed there was no significant differences between the mean performance of the two groups, were rejected if *p* was less than .05 for the *t* test statistics. A *t* test statistic *p* value of less than .05 is equivalent to the 95% confidence interval of the difference between two mean scores not containing zero (Kock, 2015). The effect size to estimate the impact of the intervention type on the outcomes was indicated by Cohen's *d*, calculated as the difference between the mean scores of two populations divided by the pooled standard deviation (Dey & Mulekar, 2018).

Normality Assumption

According to the central limit theorem, because the sample size was greater than 30, the operationalized (average) scores for perception of learning and perception of workload should be normally distributed, regardless of the underlying distribution of the raw scores (Islam, 2018). The central limit theorem did not apply to performance because it was measured with a single score on the summative assessment. Kolmogorov-Smirnov tests applying the *p* value greater than .01 level of statistical significance confirmed the normal distribution of perception of workload: $Z(66) = 1.56$, $p = .015$; perception of learning: $Z(66) = 0.91$, $p = .377$; and performance: $Z(66) = 1.18$, $p = .124$.

Test Reliability

Assumption of reliability for the perception surveys was satisfied by averaging the survey scores, which were normally distributed on a five-point Likert scale and measured at the interval level (Sullivan & Artino, 2013). Table 4 shows the scores for perception of workload, perception of learning, and performance were reliably measured, as indicated by Cronbach's alpha greater than .6 (Raharjani et al., 2022; Shi et al., 2012; Ursachi et al., 2015).

Table 4

Tests for Normality and Reliability

Statistic	Perception of workload	Perception of learning	Performance
n	66	66	66
M	2.33	4.11	36.96
SD	0.88	0.73	9.05
Z	1.56	0.91	1.18
p	.015	.377	.124
α	0.84	0.75	.68

Homogeneity of Variance Assumption

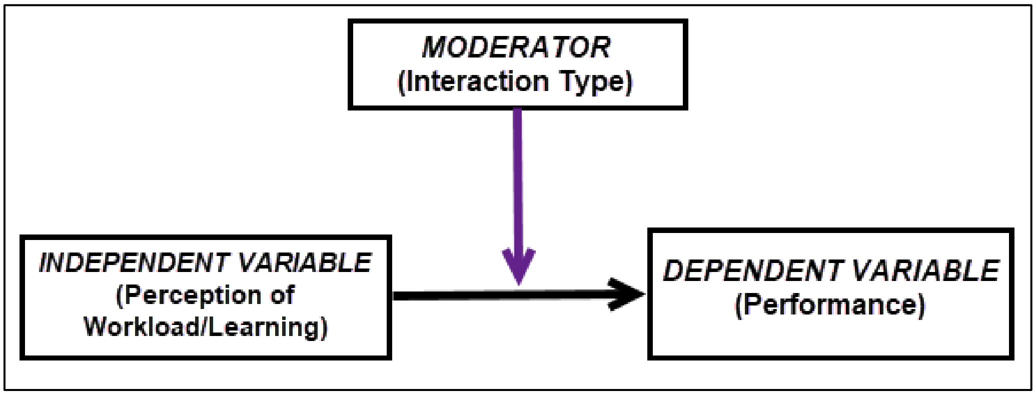
Levene's test assessed whether the variance for perception of workload, perception of learning, and performance were equal between the interaction types. The assumption of equal variances was satisfied if the *p* value was greater than .05 for Levene's test. For perception of workload, the result was significant based on an alpha value of .05, $F(1, 64) = 6.75$, $p = .012$—thus equal variances could not be assumed. However, the assumption of homogeneity is robust to violation when, as here, sample sizes are equal ($n = 33$) and relatively small (Blanca et al., 2017; Feldman, 2023; Posten, 1992). For perception of learning, the result was not significant based on an alpha value of .05, $F(1, 64) = 1.56$, $p = .216$. The result for performance also was not significant based on an alpha value of .05, $F(1, 64) = 0.619$, $p = .434$. The results suggest the assumption of homogeneity of variance was met for perception of learning and performance.

Moderator Analysis

Multiple regression was used to address Research Question 4 and Research Question 5 and test their associated hypotheses, which proposed interaction type did not significantly moderate the relationship between perception of workload/learning and performance. Multiple regression was appropriate to evaluate whether the relationship between two continuous variables (e.g., perception of workload x performance, perception of learning x performance) was dependent on (i.e., moderated by) a dichotomous moderator variable, such as interaction type (Aguinis & Gottfredson, 2010; Lund Research, 2018). The focal independent variables were perception of workload, perception of learning, and interaction type. Performance was the dependent variable. The moderator model is depicted in Figure 3.

Figure 3

Moderator Model



Note. Adapted from *Discovering Statistics Using IBM SPSS Statistics: North American Edition*, by A. Field, 2017, SAGE Publications.

The moderator hypothesis is supported when the moderator significantly affects the relationship between the independent variable and the dependent variable (Baron & Kenny, 1986; Field, 2017; Netemeyer et al., 2001). Moderator models help explain why the correlation between a predictor and an outcome is not the same for all individuals. The strength and/or direction of this correlation may depend on other categorical characteristics (e.g., interaction type) or on demographic, psychological, behavioral, or other categorical attributes of the participants (Nussbeck & Fuchs, 2017).

In the regressions, the independent variables were entered in steps. In Step 1, perception of workload/learning was entered as a predictor. In Step 2, the interaction type was entered as a predictor. In Step 3, an interaction term for perception of workload/learning by interaction type was entered as a predictor. A statistically significant *F* test result at Step 3 would indicate the relationship between perception of workload/learning and performance is moderated by interaction type (Aguinis & Gottfredson, 2010).

The relevant theoretical assumptions for hierarchical regression were checked prior to the moderator analysis. The assumption of normality was assessed with a normal P-P plot, which showed the points closely aligned along the diagonal, indicating that the residuals are approximately normally distributed. There were no outliers, as all observations had a studentized residual of less than 3 (Field, 2017). The assumption of linearity was not violated because the relationship between the predictor and the outcome variables, observed with a scatterplot, approximated a straight line. The assumption of homoscedasticity was not violated because the residuals scatterplots showing the differences between the observed and predicted values were randomly scattered on either side of their mean of zero.

The null hypothesis was rejected if the interaction type was deemed to significantly moderate the relationship between perception of workload/learning and performance (Netemeyer et al., 2001). The value of ΔR^2 at Step 3 indicated the proportion of the variance in performance explained by the moderator effect of interaction type and represented the effect size.

Definitions and Alignment of Variables

Table 5 defines the demographics, along with the dependent, independent, and moderator variables included in the research questions and hypotheses. Table 6 shows the alignment of the variables, data sources, and analysis methods used to address the research questions.

Table 5

Definitions of Variables

Variable	Functional definition	Conceptual definition	Level	Operational definition
Age	Demographic	Self-reported age	Interval	Years of age
Ethnicity	Demographic	Self-reported ethnicity	Nominal	Asian, Black, Hispanic, or White
Gender	Demographic	Self-reported gender	Nominal	Male or female
Interaction group	Moderator variable	Treatment group assignment	Nominal	Learner–content = 1 Learner–learner = 2
Performance	Dependent variable	Score for the assessment	Continuous	Score (0–50)
Perception of Learning	Independent variable	Perception of how the interaction type helped students learn	Likert scale	Average score for Q1 to Q4 (1–5)
Perception of Workload	Independent variable	Perception of how much work/effort was involved for the interaction type	Likert scale	Average score for Q1 to Q2 (1–5)

Table 6

Alignment of Research Questions, Variables, Data Sources, and Analysis Methods

Research question	Variable	Data source	Analysis method
Does interaction type impact students' perception of workload?	IV: Interaction type DV: Perception of workload	Interactive multimedia lecture, discussion questions, 2-question workload perception survey	Independent sample *t* tests
Does interaction type impact students' perception of learning?	IV: Interaction type DV: Perception of learning	Interactive multimedia lecture, discussion questions, 4-question learning perception survey	Independent sample *t* tests
Does interaction type impact performance?	IV: Interaction type DV: Performance	Interactive multimedia lecture, discussion questions, 10-item multiple selection assessment	Independent sample *t* tests
Does interaction type moderate the predictive relationship between perception of workload on performance?	IV_1: Perception of workload IV_2: Interaction type IV_3: Perception of workload x interaction type DV: Performance	2-question workload perception survey, interactive multimedia lecture, discussion questions, 10-item multiple selection assessment	Hierarchical multiple regression
Does interaction type moderate the predictive relationship between perception of learning on performance?	IV_1: Perception of learning IV_2: Interaction type IV_3: Perception of learning x interaction type DV: Performance	4-question learning perception survey, interactive multimedia lecture, discussion questions, 10-item multiple selection assessment	Hierarchical multiple regression

CHAPTER THREE

RESULTS

Two-tailed *t* tests were used to examine the impact of interaction type on learners' perception of workload, perception of learning, and performance. Hierarchical multiple regression was used to determine whether interaction type moderated the relationship between perception of workload/learning and performance.

Demographic Characteristics of Students and Group Equivalence by Interaction Type

The sample size was 66 students. The sample was divided into 33, or 50%, in both the learner–content and learner–learner groups. Tables 7, 8, and 9 summarize the demographic characteristics of the students, by interaction type, for gender, age, and race/ethnicity. Table 7 shows the sample was predominantly female (n = 57, 86.4%). The proportions of male and female students in the two groups were approximately equal, indicated by the low value of Cramer's V (.044), which was not statistically significant at .05.

Table 7

Interaction Type Versus Gender

Gender	Interaction type				Total
	Learner–content		Learner–learner		
	n	%	*n*	%	
Female	29	50.9	28	49.1	57
Male	4	44.4	5	55.6	9

Note. Cramer's V = .044, p = .72. N = 66.

The students ranged in age from 18–60 years old. Table 8 shows the most frequent age groups in the sample were 21–30 years (n = 29, 43.9%) and 31–40 years (n = 16, 24.2%). The proportions of each age group assigned to the learner–content or learner–learner types of interaction were approximately equal, indicated by the low value of Cramer's V (.126), which again was not statistically significant at .05.

Table 8

Interaction Type Versus Age

Age (years)	Interaction type				Total
	Learner–content		Learner–learner		
	n	%	*n*	%	
18–20	1	50.0	1	50.0	2
21–30	13	44.8	16	55.2	29
31–40	8	50.0	8	50.0	16
41–50	7	53.8	6	46.2	13
51–60	4	66.7	2	33.3	6

Note. Cramer's V = .126, p = .902. N = 66.

Table 9 shows the sample contained four racial/ethnic groups, of which the most frequent were White (n = 36, 55.0%) and Hispanic (n = 27, 40.9%). The proportions of each racial/ethnic group assigned to the learner–content or learner–learner types of interaction were approximately equal, indicated by the low value of Cramer's V (.215), which as before, was not statistically significant at .05. The demographic characteristics of the two groups of students were found to be similar and therefore any differences between their measured performance cannot be ascribed to differences between their gender, age, and/or race/ethnicity profiles.

Table 9

Interaction Type Versus Race/Ethnicity

Race/ethnicity	Interaction type				Total
	Learner–content		Learner–learner		
	n	%	*n*	%	
Asian	0	0.0	1	100.0	1
Black	2	100.0	0	0.0	2
Hispanic	13	48.1	14	51.9	27
White	18	50.0	18	50.0	36

Note. Cramer's V = .215, $p = .386$. $N = 66$.

Impact of Interaction Types

Research Questions 1–3 were addressed and their associated hypotheses were tested using two-tailed independent samples *t* tests to determine whether the mean scores for perception of workload, perception of learning, and performance were significantly different between the learner–content and learner–learner categories of interaction type.

Summary of Perceptions and Performance

Table 10 summarizes the scores for perception of workload, perception of learning, and performance, classified by interaction type. The mean score for perception of workload in the learner–content group ($M = 2.02$) was less than in the learner–learner group ($M = 2.65$). The mean score for perception of learning in the learner–content group ($M = 4.30$) was greater than in the learner–learner group ($M = 3.86$). The mean score for performance in the learner–learner group ($M = 37.98$) was greater than in the learner–content group ($M = 35.93$). Also shown in Table 10 are the values of Cohen's *d*; these values were calculated as the difference between the two means (M_D) divided by the pooled or average standard deviation (SD_P). All Cohen's *d* values were above 0.2.

Table 10

Comparison of Mean Scores Versus Interaction Type

Variable	Interaction type						Effect size		
	Learner–content			Learner–learner					
	M	*n*	*SD*	*M*	*n*	*SD*	M_D	SD_P	Cohen's *d*
Perception of workload	2.02	33	0.63	2.65	33	0.99	0.63	0.81	0.78
Perception of learning	4.30	33	0.59	3.86	33	0.81	-0.44	0.70	0.63
Performance	35.93	33	9.54	37.98	33	8.56	2.05	9.05	0.23

Research Question 1. Does Interaction Type Impact Students' Perception of Workload?

The result was significant based on an alpha value of .05, $t(64) = -3.12$, $p = .003$—indicating the null hypothesis can be rejected. Cohen's *d* was .78, indicating a large effect size (Cohen, 1992). This finding suggested the mean of perception of workload in the learner–content category of interaction type was significantly lower than the mean of perception of workload in the learner–learner category. The results are presented in Table 11.

Table 11

Impact of Interaction Type on Perception of Workload

	Learner–content			Learner–learner					
Variable	*M*	*SD*	*n*	*M*	*SD*	*n*	*t*	*p*	*d*
Perception of workload	2.02	.63	33	2.65	0.99	33	-3.12	.003	0.78

Note. $n = 66$. Degrees of freedom for the *t* statistic = 64. *d* represents Cohen's *d*.

Research Question 2. Does Interaction Type Impact Students' Perception of Learning?

The result was significant based on an alpha value of .05, $t(64) = 2.57$, $p = .013$—indicating the null hypothesis can be rejected. Cohen's *d* was .63, indicating a medium–large effect size (Cohen, 1992). This finding suggested the mean of perception of learning in the learner–content category of interaction type was significantly greater than the mean of perception of learning in the learner–learner category. The results are presented in Table 12.

Table 12

Impact of Interaction Type on Perception of Learning

	Learner–content			Learner–learner					
Variable	*M*	*SD*	*n*	*M*	*SD*	*n*	*t*	*p*	*d*
Perception of learning	4.30	0.59	33	3.86	0.81	33	2.57	.013	0.63

Note. *n* = 66. Degrees of freedom for the *t* statistic = 64. *d* represents Cohen's *d.*

Research Question 3. Does Interaction Type Impact Students' Performance?

The result was not significant based on an alpha value of .05, $t(64) = -0.92$, $p = .363$—indicating the null hypothesis cannot be rejected. Cohen's *d* was .23, indicating a small effect size (Cohen, 1992). This finding suggested the mean of performance in the learner–content category of interaction type was not significantly lower than the mean of performance in the learner–learner category. The results are presented in Table 13.

Table 13

Impact of Interaction Type on Performance

	Learner–content			Learner–learner					
Variable	*M*	*SD*	*n*	*M*	*SD*	*n*	*t*	*p*	*d*
Performance	35.93	9.54	33	37.98	8.56	33	-0.92	0.363	0.23

Note. *n* = 66. Degrees of freedom for the *t* statistic = 64. *d* represents Cohen's *d.*

Moderator Effects of Interaction Type

Research Question 4. Does Interaction Type Moderate the Relationship Between Students' Perception of Workload and Performance?

The *F* test for Step 3 was not significant at an alpha value of .05, F (1, 62) = 0.46, p = .500, ΔR^2 = .01—suggesting adding interaction type by perception of workload did not account for a significant amount of variation in performance. Thus, there is insufficient evidence of a moderator effect of interaction type on the relationship between perception of workload and performance. Table 14 presents the results for the model comparisons. The nonsignificant *F* statistic indicated this model is not a good fit to the data.

Table 14

Model to Predict Moderation of Performance Versus Perception of Workload

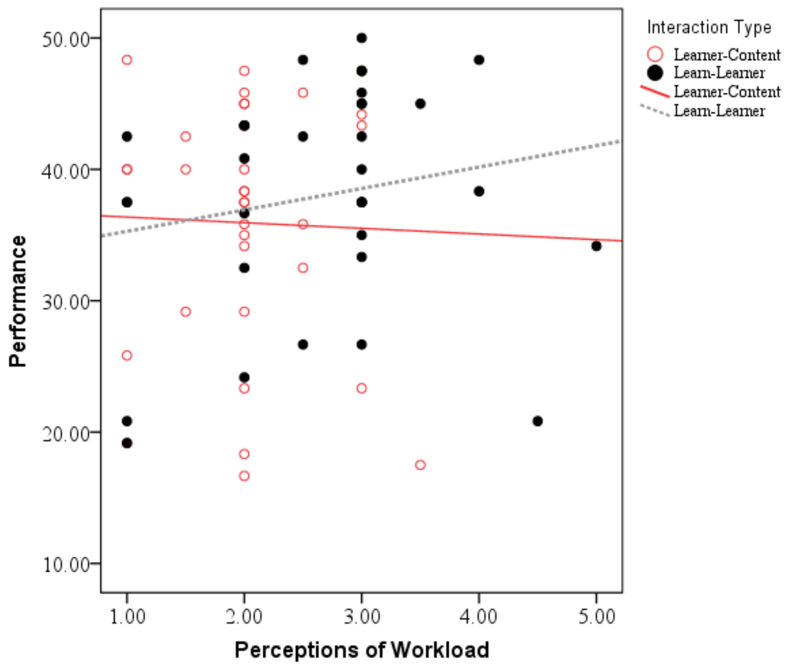
Model	R^2	df_{mod}	df_{res}	F	p	ΔR^2
Step 1	.02	1	64	1.08	.303	.02
Step 2	.02	1	63	0.33	.566	.01
Step 3	.03	1	62	0.46	.500	.01

Note. Each step was compared to the previous model in the hierarchical regression analysis.

Figure 4 illustrates the relationship between perception of workload and performance; the linear regression lines represent the learner–content and learner–learner groups. The two lines are almost horizontal, implying that interaction type does not moderate the strength and/or direction of the correlation between perception of workload and performance.

Figure 4

Plot of Perception of Workload Versus Performance



Research Question 5. Does Interaction Type Moderate the Relationship Between Students' Perception of Learning and Performance?

The *F* test for Step 3 was significant at an alpha value of .05, F (1, 62) = 8.84, p = .004, ΔR^2 = .123—suggesting adding perception of learning by interaction type explained an additional 12.27% of the variation in performance. The finding also suggested there is evidence to support the existence of a moderator effect of interaction type on the relationship between perception of learning and performance (Netemeyer et al., 2001). Table 15 presents the results for the model comparisons. The statistically significant *F* statistic indicated this model is a good fit to the data.

Table 15

Model Comparisons for Variables Predicting Performance

Model	R^2	df_{mod}	df_{res}	ΔF	p	ΔR^2
Step 1	.00	1	64	0.04	.846	.00
Step 2	.02	1	63	1.04	.312	.02
Step 3	.14	1	62	8.84	.004	.12

Note. Each step was compared to the previous model in the hierarchical regression analysis.

The results for Step 3 of the regression are shown in Table 16. The negative regression coefficient of the interaction term (ß = -9.50) suggested the potential change of the relationship between perception of learning and performance across the two interaction groups.

Table 16

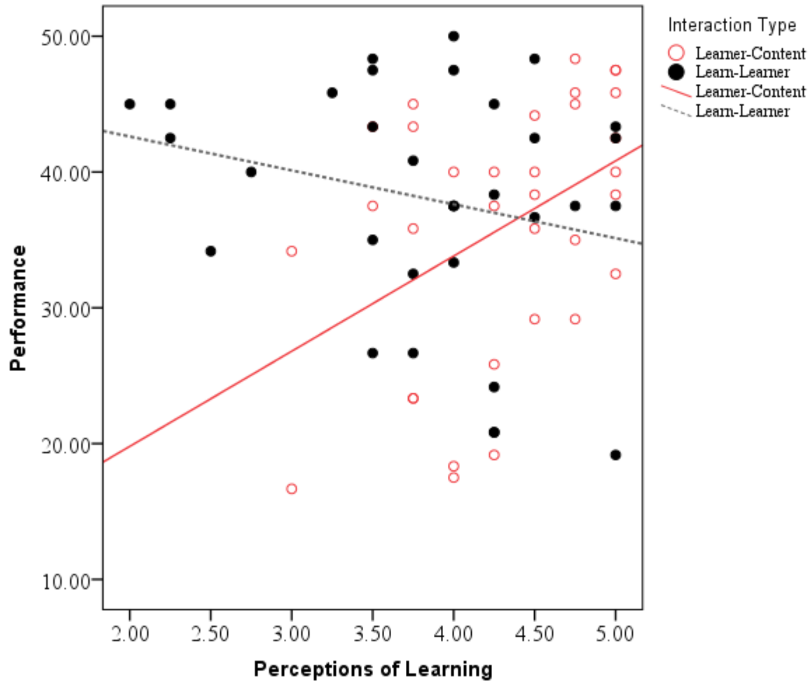
Model to Predict Moderation of Performance Versus Perception of Learning

Predictors	Unstandardized coefficients		t	p	95% CI	
	ß	*SE*			Lower	Upper
(Constant)	-36.04	23.62	-1.53	.132	-88.46	12.63
Perception of learning	16.51	5.49	3.00	.004	5.63	28.08
Interaction type	41.82	13.44	3.11	.003	14.71	70.16
Moderator effect	-9.50	3.19	-2.97	.004	-15.82	-3.24

Figure 5 illustrates the relationship between perception of learning and performance; the linear regression lines represent the learner–content and learner–learner groups. The two lines are not parallel, but diverge in different directions, suggesting interaction type does moderate the strength and direction of the correlation between perception of learning and performance.

Figure 5

Plot of Perception of Learning Versus Performance



In the learner–content group, the level of performance increased linearly with respect to an increase in the level of the perception of learning. In contrast, in the learner–learner group, the level of performance decreased linearly with respect to an increase in the level of the perception of learning. Because of the potential change and differing directions across the two interaction types, subgroup regression analyses by interaction type were conducted to examine the focal relationship between perception of learning and performance in each of those two interaction groups, respectively.

For the learner–content group, the results were significant at an alpha value of .05, $F(1,31) = 7.13$, $p = .012$, $R^2 = .187$—suggesting approximately 18.7% of the variance in performance is explained by perception of learning. Table 17 shows the regression results for the learner–content group. Perception of learning significantly predicted performance, $B = 7.01$, *t*(31) = 2.67, *p* = .012. This indicated on average, a one-level increase in perception of learning will increase performance by 7.01 points.

Table 17

Model to Predict Performance Versus Perception of Learning for Learner–Content Interaction Type

Predictors	Unstandardized coefficients		*t*	*p*	95% CI	
	ß	*SE*			Lower	Upper
(Constant)	5.78	11.39	0.51	.615	-17.46	29.02
Perception of learning	7.01	2.62	2.67	.012	1.65	12.36

For the learner–learner group, the results were not significant at an alpha value of .05, $F(1,31) = 1.82$, $p = .187$, $R^2 = .06$—suggesting that perception of learning did not explain a significant proportion of variation in performance. Table 18 shows the regression results for the learner–learner group.

Table 18

Model to Predict Performance Versus Perception of Learning for Learner–Learner Interaction Type

Predictors	Unstandardized coefficients		*t*	*p*	95% CI	
	ß	*SE*			Lower	Upper
(Constant)	47.60	7.29	6.53	< .001	32.74	62.46
Perception of Learning	-2.50	1.85	-1.35	.187	-6.27	1.28

Summary

Research Question 1. Does interaction type impact students' perception of workload?

Hypothesis 1. There was a significant difference in perception of workload, with a large effect size, between the learner–content interaction group and the learner–learner interaction group.

Research Question 2. Does interaction type impact students' perception of learning?

Hypothesis 2. There was a significant difference in perception of learning, with a medium–large effect size, between the learner–content interaction group and the learner–learner interaction group.

Research Question 3. Does interaction type impact performance?

Hypothesis 3. There was no significant difference in performance, and a small effect size, between the learner–content interaction group and the learner–learner interaction group.

Research Question 4. Does interaction type moderate the relationship between perception of workload and performance?

Hypothesis 4. Interaction type did not significantly moderate the relationship between perception of workload and performance.

Research Question 5. Does interaction type moderate the relationship between perception of learning and performance?

Hypothesis 5. Interaction type significantly moderated the relationship between perception of learning and performance, accounting for an additional 12.27% of the variation in performance between the learner–content interaction group and the learner–learner interaction group. Subgroup regression analyses suggest 18.70% of the variance in performance for the learner–content group was explained by students' perception of learning.

CHAPTER FOUR

DISCUSSION

This study examined the impact of interaction types on students' perception of workload, perception of learning, and performance in an online, asynchronous, undergraduate-level setting of formal distance education (DE). The primary aim was to determine whether learner–content interaction can substitute for learner–learner interaction with no significant impact on learner performance (Anderson, 2003a); the results suggest it can.

Substitutivity and Performance

Prior research has shown increasing the quantity of any type of interaction in the presence of some other type tends to increase performance (Bernard et al., 2009; Graham & Massyn, 2019). That earlier research focused on students' perception of their performance without data that measured and verified that performance (Bernard et al., 2009; Persky et al., 2020). This study, however, appears to be the first to provide evidence of the substitutivity of interaction types posited by Anderson's (2003a) first thesis. Thus, the chief contribution from this finding on measured performance is support from an experimental design with randomized assignment for scalable course designs that facilitate knowledge acquisition through learner–content interactions in lieu of learner–learner interactions.

By measuring performance, this study avoided the often-inaccurate perceptions reported by novice learners (Dunning et al., 2003; Emory & Luo, 2020; Pennycook et al., 2017; Stone et al., 2000). This study did not explore reasons for performance equivalence. However, one logical explanation is that both treatment groups received the same content through the same media and then received equivalent feedback on their understanding before taking the summative assessment.

Perception of Workload

In addition to evidence of performance associated with the interaction types, this study also explored students' perceptions of the workload imposed by the interaction type. Research to date has been scant on learners' perception of the workload associated with specific interaction types and its correlation to measured performance. Within the available literature, the focus has been on perceptions of overall workload in different DE settings (Beena & Sony, 2022; Razami & Ibrahim, 2021; Smart & Cappel, 2006; Smidt et al., 2014; Valenta et al., 2001). In this study, the inquiry was instead focused directly on the perceived workload for the specific interaction type rather than the workload for the course overall.

The data from this study suggested students in the learner–learner group found the generative learning activity of creating, sharing, and critiquing their peers' vignettes in the discussion area to be significantly more work than the generative learning activity of interactive video experienced by the learner–content group. Thus, although there was no significant difference between the two groups' performance, the learner–learner group perceived they had to work harder to achieve that performance.

As with the performance measure, this study did not seek to elicit reasons the learner–learner group felt it worked harder. Prior research regarding attitudes about workload in online courses has clearly shown discussion groups are viewed as work intensive. This has been due, at least in part, to those discussions being designed with structured prompts that prescribe the form and content of the response. And although this type of discussion format facilitates an instructor's consistent evaluation and feedback of responses, it limits students' ability to be more creative, thereby contributing to students viewing discussions as "busywork" (Smidt et al., 2014, p. 51). In this study, students were not constrained in the creativity of their response; yet, they still viewed it as more work. It is plausible they viewed it as such partly because students in the learner–learner group must call upon a wider range of skills than the learner–content group to interact. All students do not have these skills in equal measure: imagination, verbalizing, writing skills, typing skills, and general computer usage skills. The need for students to engage in those additional cognitive and behavioral activities necessarily imposes a higher, and essentially extraneous, workload to achieve the same performance. This extraneous load may help explain why subjects in a prior study involving discussion in DE courses reported the time and effort needed to complete the work was not worth the learning they gained (Smart & Cappel, 2006).

Perception of Learning

Students' perception of how well the interaction type helped them learn and thereby achieve their performance level was also examined in this study. Researchers have found students rated learner–learner interaction as the least important of the three interaction types (Cabral, 2016; Miyazoe & Anderson, 2010; Rhode, 2009). Similarly, Katsarou and Chatzipanagiotou (2021) found learner–content interaction correlated to learner satisfaction and course completion whereas learner–learner interaction did not. However, literature has not squarely addressed whether students believe the interaction helped them achieve a measured level of performance. This study helps fill that gap.

Students in the learner–content group indicated a significantly greater perception of the learning they achieved from the interaction than did students in the learner–learner group. This finding was curious given there was no significant difference in the measured performance of the two groups. This seeming contradiction may be related to students' perception of how hard they worked to achieve that learning. As noted, the learner–learner group rated the workload of their interaction higher than did the learner–content group. If one believes an interaction method requires more work to achieve a level of performance, then perhaps they perceive that interaction as less efficient in helping them achieve that performance. Or, perhaps, because they believe they worked harder, students feel they must have learned more. Notwithstanding the reported perceptions and their possible bases, research has previously found, and the moderator analysis discussed in the following section found, students' perception of how well their effort or an interaction type helps them learn is not always supported by the performance data.

Interaction Type, Perception, and Performance

The secondary aim of this study was to search for any relationship between perceptions and performance and determine whether any such relationship is moderated by interaction type.

Moderator Effect of Interaction Type: Perception of Workload Versus Performance

Students' perception of workload did not explain a significant amount of variance in their performance. Furthermore, there was insufficient evidence to support a moderator effect of interaction type on the relationship between the perception of workload and performance. This finding suggests even though students perceived learner–learner interactions to be more work, neither the perception of workload, nor the interaction type, nor their combined effect explains much about the reason for their performance.

This finding is significant because it fills a gap in DE perception research by mapping perceived workload to measured, rather than perceived, performance. In doing so, it provides evidence that perceived workload alone, regardless of the required interaction type, does not significantly impact performance. This finding stands in contrast to prior research where students attributed their increased sense of workload to their perceived increase in performance (Bernard et al., 2009; Katsarou & Chatzipanagiotou, 2021; Zawacki-Richter & Naidu, 2016). If learner–content interaction is perceived as less work while producing the same result, and if interpersonal interactions do not further an instructional or other relevant goal (Anderson, 2003a; Daniel & Marquis, 1979; Drouin, 2008), instructional designers have empirical support to inform their choices about the appropriate mix of interaction types in DE courses (Beer, 2019; Daniel & Marquis, 1979).

Moderator Effect of Interaction Type: Perception of Learning Versus Performance

In contrast to finding no moderator effect of interaction type by perception of workload on performance, interaction type did significantly moderate the relationship between perception of learning and performance. In the learner–content group, performance increased linearly with respect to an increase in the perception of learning while in the learner–learner group performance decreased linearly with respect to an increase in the perception of learning. In other words, the more strongly students in the learner–content group perceived the interaction helped them learn, the better they performed. Thus, their perception they were learning was supported by their measured performance. Conversely, the perception of students in the learner–learner group that the interaction helped them learn was not supported by their performance. Thus, even though there was no significant difference in performance between the two groups, students in the learner–learner group misperceived the learning benefit of the interaction type. In this study, as shown throughout the literature, learners—especially novice learners—are often unable to accurately gauge what learning activity is effective or assess their own competence level (Dunning et al., 2003; Emory & Luo, 2020; Pennycook et al., 2017).

Implications for Instructional Design and Technology Practitioners

In a formal DE setting, students are often enrolled in multiple courses related to a program of study. The adult learners in these contexts often choose DE courses specifically for the flexibility they provide and because they do not desire a high degree of interpersonal activity

(Drouin, 2008). Indeed, regardless of personal reasons for choosing the DE modality, market data make clear that although in-person enrollment has continued to decline across the higher education landscape, enrollment in DE courses has grown (Garrett et al., 2023). At the same time, the resources needed to support DE have not kept pace (Garrett et al., 2023), which will limit the ability of institutions to meet the demand for well-trained instructors to teach well-designed courses. Thus, as DE offerings expand, designers should be mindful of conflicts that can arise between pedagogical preferences related to interaction in DE courses and untested assumptions, perceptions, and the reason learners often choose DE (Anderson, 2003b; Daniel & Marquis, 1979; Prupis, 2023; Stone et al., 2000).

As part of their front-end analysis, designers should determine whether the learning experience being developed requires interpersonal interaction to accomplish an instructional objective or ancillary purpose, such as building a sense of community or collaboration. If not, findings from this study suggested learner–content interactions impose a lower perceived workload and a higher perceived level of learning that correlates to higher measured performance and can be substituted for learner–learner interactions without impacting performance (Beer, 2019; Daniel & Marquis, 1979; Mager, 1997).

For this study, sharing vignettes through discussion questions in the LMS and interactive multimedia were deliberately chosen to operationalize the interaction types. Just as designers should assess the need for interpersonal interaction, they should also evaluate what tools, techniques, and methods are best suited to operationalize that interaction when it is needed, as well as purposefully select the way learners will interact with the content. The technology used to provide the learner–content interactions for this study consisted of relatively inexpensive and easy-to-use software. The affordability and simplicity of these tools makes them accessible to all but the most budget-constrained designer. For those designers with more ample resources, more robust tools provide richer content experiences, more interaction options, more metrics, and integrate into the modern LMS. The combined effect of (a) relieving DE instructors of the workload associated with moderating learner–learner interaction and (b) using learner–content tools that provide real-time feedback to students and integration with the LMS creates more capacity for DE instructors. That new-found capacity can be used to increase the scale of asynchronous, online courses by reducing the magnitude of interaction constraints such as cost, time, and complexity without increasing delivery cost or decreasing learner performance (Kasch et al., 2017, 2021). Instructors can then reframe their role to better provide learners with the interpersonal interactions shown to support learner motivation, self-confidence, and academic performance (Bernard et al., 2009; Kim, 2022; Qaqish et al., 2020; Winterer et al., 2020).

Limitations

The findings for this study were based on data from adult learners in an undergraduate, law-related occupational program, all of whom obtained admission to the program by demonstrating academic readiness with validated criteria (Hauert et al., 2021). Therefore, results may not be generalizable to different populations of learners in different educational contexts. Additionally, the content learners interacted with consisted of explicit, declarative knowledge; and thus, the study's findings may not be replicable when testing the substitutivity of interactions with other knowledge types. The study used data from a single instructional episode over the span of 1 week. Because participants had some autonomy to determine the pace of their activities during the week, the effect of timing between their interactions, feedback, and assessments could be a factor in their performance and reported perceptions. The results also suggested much remains to be understood about the reasons for learners' perceptions that could not be captured solely through the quantitative data. The finding of no significant difference in performance despite the significant difference in perceived workload and learning, along with the dichotomy of how these variables were impacted by interaction type, suggests qualitative data are needed to better contextualize the findings.

Future Research

Although this study appears to provide the first empirical test using an experimental design with random assignment supporting the substitutive prong of Anderson's (2003a) interaction equivalency theory, additional research is needed. The next logical step is to examine the substitutivity of interaction types for other knowledge domains, content areas, and contexts. This study examined the substitutivity of learner–content and learner–learner interaction, leaving a research gap related to the substitutivity of the learner–instructor dimension. It also seems important to explore more deeply, such as through a phenomenological study, what *workload* and *learning* mean in the mind of learners.

Interviews, for example, may clarify what tasks learners believe contribute to their workload. In turn, researchers may better understand the contribution created by specific cognitive and behavioral activities inherent in the interaction type (e.g., imagining, typing, manipulating the LMS). Similarly, interviews or surveys may help researchers understand why learners perceive the impact of interaction types on their learning differently from what data have shown has no such measurable effect. Factors to explore might include the perceived credibility of the content and feedback source, as well as the impact from the structure or presentation of the content and feedback.

Finally, it seems necessary to examine the outcome to be facilitated by an interaction type and the method to best achieve it. Regulating conduct and flow of a course through learner–

instructor interaction is likely not comparable to building community through learner–learner interaction. Likewise, community building and other social constructivist dynamics are unlikely to be comparable to conveying knowledge through learner–content interaction.

Hence, it may well be possible to reduce or eliminate certain interaction types depending on the instructional goal. But, if measurable acquisition of knowledge is the desired outcome, then content must be provided regardless of whether human–human interaction occurs. This has been a rich area of scientific focus since at least 1928 when Pressey patented one of the first teaching machines—devices designed to present content, allow students to respond to the content, and provide students feedback, all without instructor intervention (Benjamin, 1988). Thus, future research on substituting interaction types must consider the instructional goal when determining how to deliver the content. Advances in technology, especially artificial intelligence, and its ability to create ultra-high-fidelity analogs of human voices and personas, may make it possible to test the substitutivity of not only interaction types, but also the agents (Wagner, 1994, 1997) engaged in the interaction.

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Appendix A – Informed Consent Form

INFORMED CONSENT DOCUMENT

OLD DOMINION UNIVERSITY

PROJECT TITLE: ASSESSING THE IMPACT OF SUBSTITUTING INTERACTION TYPES: AN EMPIRICAL STUDY OF THE INTERACTION EQUIVALENCY THEORY

INTRODUCTION

The purposes of this form are to give you information that may affect your decision whether to say YES or NO to participation in this research, and to record the consent of those who say YES. The name of this study is "Assessing the impact of substituting interaction types: An empirical study of the interaction equivalency theory."

RESEARCHERS

Principal Investigator: Dr. Tian Luo (Assistant Professor, Old Dominion University, STEM Education and Professional Studies)

Investigator: Scott A. Hauert (Your instructor for this class at Phoenix College).

DESCRIPTION OF RESEARCH STUDY

The purpose of this study is to explore whether different activities differently affect how a student learns the material. The study also explores whether students feel different activities involve different levels of work or feel different activities are more or less helpful to them in learning the material. It is proposed that students can either view a video lecture with interactive quiz questions or view a non-quiz version of the lecture but participate in class discussion about the material and achieve the same results on a quiz.

There is no additional or different work involved inside or outside of the class. During the week that covers the topic of insurance, you will complete the same assigned material as everyone else in your class. You will also complete the same quiz over the material for the week as your classmates. These are the same activities that you complete every week in the course. For this one week, you will also complete a six-question survey that asks you to rate your perception of the amount of work involved in the activities and your perception of how helpful those activities were in learning the material.

Only the overall, anonymous, aggregated results will be used in the study. There will be approximately 80 people in the study.

By participating in this study, you will be completing the exact same work during the week as you would if you did not participate in the study.

To participate in the study, you are being asked only to consent to having your anonymized results combined (aggregated) with those of everyone else so that no single student's information can possibly be identified. If you choose to not participate, you will still complete the same coursework, but your anonymized results will not be combined with those that do participate and your anonymized results will not be used in the study.

EXCLUSIONARY CRITERIA

You must be enrolled in LAS101 or LAS212 in the fall 2022 semester with Scott Hauert as your instructor to participate in the study.

RISKS AND BENEFITS

RISKS: There are no known or anticipated risks to viewing video lectures, participating in discussion, taking a quiz, or completing a survey. No personally identifiable or private information about a student will be reported in the study.

BENEFITS: This study will be used to further the general knowledge on what type of learning activities are effective in an online course and used to help improve future courses.

COSTS AND PAYMENTS

There are no costs involved in participating in the study. There are no payments or compensation for participating in the study.

NEW INFORMATION

If the researchers find new information during this study that would reasonably change your decision about participating, then they will give it to you.

CONFIDENTIALITY

All information about students in the student will be anonymized and aggregated with that of entire class so that no single student's information can be identified. The information collected will only be used for this research and will not be shared with other researchers now or in the future. The results of this study may be used in reports, presentations, and publications; but the researcher will not identify you. Of course, as is the case with any student's educational records regardless of whether they are in a study, your records may be subpoenaed by court order or inspected by government bodies with oversight authority.

WITHDRAWAL PRIVILEGE

Participation in this research study is voluntary. It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study at any time. Your decision will not affect your relationship with Old Dominion University, or otherwise cause a loss of benefits to which you might otherwise be entitled.

COMPENSATION FOR ILLNESS AND INJURY

If you say YES, then your consent in this document does not waive any of your legal rights. However, in the event of any physical or mental injuries arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in any research project, you may contact Dr. Tian Luo at XXX-XXX-XXXX, Dr. John Baaki the current IRB chair at XXX-XXX-XXXX at Old Dominion University, or the Old Dominion University Office of Research at XXX-XXX-XXXX who will be glad to review the matter with you.

VOLUNTARY CONSENT

By signing this form, you are saying several things. You are saying that you have read this form or have had it read to you, that you are satisfied that you understand this form, the research study, and its risks and benefits. The researchers should have answered any questions you may have had about the research. If you have any questions later on, then the researchers should be able to answer them.

If you have questions about this study, please contact:

Principal Investigator: Dr. Tian Luo at XXX-XXX-XXXX or xxxxx@odu.edu

or

Scott Hauert at XXX-XXX-XXXX or xxxxx@xxxxx.edu

If at any time you feel pressured to participate, or if you have any questions about your rights or this form, then you should call or email Dr. John Baaki, the current IRB chair, at XXX-XXX-XXXX or xxxxx@odu.edu, or the Old Dominion University Office of Research, at XXX-XXX-XXXX.

And importantly, by signing below, you are telling the researcher YES, that you agree to participate in this study. The researcher should give you a copy of this form for your records.

Subject’s Printed Name & Signature	Date

INVESTIGATOR’S STATEMENT

I certify that I have explained to this subject the nature and purpose of this research, including benefits, risks, costs, and any experimental procedures. I have described the rights and protections afforded to human subjects and have done nothing to pressure, coerce, or falsely entice this subject into participating. I am aware of my obligations under state and federal laws, and promise compliance. I have answered the subject’s questions and have encouraged him/her to ask additional questions at any time during the course of this study. I have witnessed the above signature(s) on this consent form.

Investigator’s Printed Name & Signature	Date

Appendix B – Survey Questions for Learner–Content Group

Perception of Learning Questions

Question 1

Viewing the video lecture and attempting the questions helped me understand the material.

- ○ Strongly disagree
- ○ Disagree
- ○ Neither agree nor disagree
- ○ Agree
- ○ Strongly agree

Question 2

Reading and thinking about the explanation displayed after each question helped me understand the material.

- ○ Strongly disagree
- ○ Disagree
- ○ Neither agree nor disagree
- ○ Agree
- ○ Strongly agree

Question 3

On the occasion(s) that I chose to replay parts of the lecture related to questions I missed or that I wanted to view again it helped me understand the material.

- ○ Strongly disagree
- ○ Disagree
- ○ Neither agree nor disagree
- ○ Agree
- ○ Strongly agree

Question 4

Viewing the video lecture and doing the quiz questions built-in to the lecture helped me score higher on the quiz at the end of the week.

- ○ Strongly disagree
- ○ Disagree
- ○ Neither agree nor disagree
- ○ Agree
- ○ Strongly agree

Perception of Workload Questions

Question 5

Viewing the video lecture and attempting the questions that were part of the lecture was a lot of work.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

Question 6

Reading and considering the explanation displayed after answering each question was a lot of work.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

Appendix C – Survey Questions for Learner–Learner Group

Perception of Learning Questions

Question 1

Reading the question, considering the material, and then preparing and posting my own, original responses in the discussion group helped me understand the material.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

Question 2

Reading the response from at least one of my classmates to the discussion question, considering that response, and then preparing and posting feedback to my classmate helped me understand the material.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

Question 3

On the occasion(s) that I chose to review feedback I received from my classmates about my posts in the discussion group it helped me understand the material.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

Question 4

Participating in the discussion group helped me score higher on the quiz at the end of the week.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

Perception of Workload Questions

Question 5

Reading the questions, considering the material, and then preparing my own, original responses in the discussion group was a lot of work.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

Question 6

Reading the response from at least one of my classmates to the discussion, considering that response, and then preparing and posting feedback to a classmates was a lot of work.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

Appendix D – Performance Assessment

Q1 – Assume you have only automobile liability insurance. At least one of the following statements is true. Choose all that are true.

Your coverage will apply to damage to your car and injuries to your body in an accident that is your fault.

Your coverage will apply to damages to your car and injuries to your body in an accident that is the other driver's fault.

*Your coverage will apply to damage to the other driver's car and injuries to the other driver's body in an accident that is your fault.

Your coverage will apply to damage to the other driver's car and injuries to the other driver's body in an accident that is the other driver's fault.

Q2 – Assume you have automobile liability and comprehensive insurance. At least one of the following statements is true. Choose all that are true.

Your coverage will apply to damage to your car if it is struck by another driver while parked in front of your house.

*Your coverage will apply to damage to your car if someone takes a knife and deliberately cuts all your tires while parked at work.

Your coverage will apply to damage to your car if you strike a guard rail while driving to work.

*Your coverage will apply to damage caused to a traffic signal if you accidentally strike it while driving to work.

Q3 – Assume you have only automobile liability and collision insurance. At least one of the following statements is true. Choose all that are true.

*Your coverage will apply to damage to your car if it is struck by another driver while parked in front of your house.

Your coverage will apply to damage to your car if someone takes a knife and deliberately cuts all your tires while parked at work.

*Your coverage will apply to damage to your car if you accidentally strike a guard rail while driving to work.

*Your coverage will apply to damage caused to a traffic signal if you accidentally strike it while driving to work.

Q4 – Assume you have only automobile liability and uninsured motorist insurance for property damage and personal injury. At least one of the following statements is true. Choose all that are true.

Your coverage will apply to damage from your uninsured neighbor’s tree falling on your car.

Your coverage will apply to damage to your uninsured neighbor’s car from your tree falling on it.

*Your coverage will apply to damage to your car from your uninsured neighbor accidentally backing into your car with their car.

Your coverage will apply to damage to your neighbor’s car from you deliberately ramming their car with your car.

Q5 – Assume you have automobile liability insurance that covers $10,000 in property damage and $10,000 in personal injuries, as well as underinsured motorist insurance for $10,000 in property damage only. Assume your neighbor has $10,000 liability insurance for property damage and $10,000 in personal injury. At least one of the following statements is true. Choose all that are true.

Your coverage will apply to damage to your car from the neighbor's tree falling on it if the damage exceeds $10,000.

Your coverage will apply to damage from a tree in your own yard falling on the neighbor's car if the damage exceeds $10,000.

*Your coverage will apply to damage to your car from the neighbor accidentally backing into your car with their car if the damage exceeds $10,000.

Your coverage will apply to damage to your car from your neighbor deliberately taking a knife and cutting all your tires if the damage exceeds $10,000.

Q6 - Assume that your car has a fair market value of $50,000. It is struck by another vehicle while parked in front of your house; you were sitting in the car at the time. The other vehicle flees the scene and is never identified. Your car suffers $20,000 in property damage. You suffer $20,000 in personal injuries. At least one of the following is true. Choose all that are true.

If you have only liability coverage of $10,000 for property damage and $10,000 for personal injury it can be used to pay part of the property damage to your car and part of your personal injuries.

*If you have liability coverage of $10,000 for property damage and $10,000 for personal injury, as well as collision coverage of $10,000, but no uninsured motorist coverage, the collision coverage can be used to pay part of the property damage to your car.

*If you have liability coverage of $10,000 for property damage and $10,000 for personal injury, as well as uninsured coverage in the same amounts, but no collision coverage, the uninsured coverage can be used to pay for part of the property damage to your car and part of your personal injuries.

If you have liability coverage of $10,000 for property damage and $10,000 for personal injury, as well as comprehensive coverage of $10,000, the comprehensive coverage can be used to pay part of the property damage to your car.

Q7 - Assume that you purchased a used car one week ago and paid $10,000. The car has a fair market value of $7,000. Your car is damaged when it is struck from the rear by another vehicle while you are driving to work. In will cost $10,000 to repair the damage. You are not injured. At least one of the following statements is true. Choose all that are true.

> *For any insurance coverage you have that applies to this loss, it will pay up to $7,000 less any deductible that applies.
>
> For any insurance coverage you have that applies to this loss, it will pay up to $10,000 less any deductible that applies.
>
> *You need collision coverage.
>
> You need comprehensive coverage.

Q8 - Assume that you purchased a used car last week and paid $10,000. The car has a fair market value of $15,000. You strike a moose that ran in front of your car, resulting in $12,000 of property damage. You are not injured. At least one of the following statements is true. Choose all that are true.

> For any insurance coverage you have that applies to this loss, it will pay up to $10,000 less any deductible that applies.
>
> *For any insurance coverage you have that applies to this loss, it will pay up to $12,000 less any deductible that applies.
>
> *You need comprehensive coverage.
>
> You need collision coverage.

Q9 - Assume that your car has a fair market value of $50,000. You negligently collide with the rear of another vehicle (i.e., it is your fault). The other vehicle has a fair market value of $50,000. Both cars suffer $20,000 in damage. You and the other driver each suffer $100,000 in personal injuries. At least one of the following statements is true. Choose all that are true.

> If you have liability coverage of $10,000 in property damage/$50,000 personal injury, it can be used to pay at least part of your own property damage and personal injuries.
>
> *If you have liability coverage of $10,000 in property damage/$50,000 personal injury, it can be used to pay at least part of the other driver's property damage and personal injuries.
>
> *If the other driver does not have underinsured motorist coverage but does have collision coverage of $5,000, it can be used to pay at least part of their property damage.
>
> *If the other driver does not have collision coverage but does have underinsured coverage of $5,000 in property damage/$5,000 personal injury, it can be used to pay at least part of the other driver's property damage and personal injuries.

Q10 - Assume that your car has a fair market value of $20,000. You negligently collide with the rear of another vehicle (i.e., it is your fault). The other vehicle has a fair market value of $40,000. It will cost $50,000 to repair your car and $50,000 to repair the other driver's car. You and the other driver each suffer $100,000 in personal injuries. At least one of the following statements is true. Choose all that are true.

If you have liability coverage of $100,000 in property damage/$300,000 personal injury, the other driver will receive $50,000 toward their property damage.

*If you have liability coverage of $100,000 in property damage/$300,000 personal injury, the other driver will receive $40,000 toward their property damage.

If you have liability coverage of $100,000 in property damage/$300,000 personal injury, the other driver will receive $300,000 toward their personal injuries.

*If you have liability coverage of $100,000 in property damage/$300,000 personal injury, the other driver will receive $100,000 toward their personal injuries.

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