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ENHANCING HIGHER EDUCATION IN THE DIGITAL AGE: THE SEVEN KEY AFFORDANCES OF E-LEARNING

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ABSTRACT

This study uses a combination of qualitative and quantitative methodologies to examine the connections between student motivation and the incorporation of essential e-learning features while also identifying differences in various learning environments. A study conducted on a sample of 1500 students revealed that widespread access, collaborative work with peers, projects requiring multiple skills, and the integration of adaptive support all positively impacted motivation levels. The impact was most pronounced for customised differentiation. Subsequent focus groups were conducted with 80 technical and soft sciences learners, comparing fully online and blended learning methods. The findings revealed that technical disciplines emphasised simulation and collaborative forums, facilitating widespread practice and error correction.

Meanwhile, humanities students preferred organised incorporation amid a surplus of online content. Blended enrolments showed lower use of self-directed affordance due to decreased personal accountability compared to purely online peers relying on distinction. The project proposes evaluating the local patterns and combinations that impact achievement, investigating the display of metacognitive data and virtual mentorship systems, and deliberately fostering Communities of Enquiry to utilise their potential benefits fully. Significant constraints arise from the fact that the causal processes have not been empirically verified. Investigating the connections between specific combinations of affordances and long-term performance provides valuable opportunities for further study.

KEYWORDS: Accessibility, Authenticity, Collaboration, Flexibility, Interactivity, Personalisation, Scalability and Ubiquity

1. INTRODUCTION

1.1 Background on E-learning Evolution

The higher education sector has experienced significant and rapid change due to the digitalisation of instructional materials and the rapid advancement of interactive internet technology in recent decades (Martinez-Garcia et al., 2023). The initial computer-based learning activities, such as basic drill-and-practice or linear multimedia lessons, have evolved into advanced blended and online learning environments that facilitate collaborative constructivist paedagogies (Li, 2018). Examining significant advancements helps to highlight the important reasons that are driving the rise and widespread adoption of e-learning in mainstream education (Martinez-Garcia et al., 2023).

Early emergence began in the 1960s/1970s when enthusiasm around leveraging instructional design, cognitive science and computer science to enhance Learning initially seeded the computer-assisted instruction (CAI) movement (Bai et al., 2020). However, prohibitively expensive hardware, programming demands and minimal classroom integration limited CAI's early reach. More immersive adoption began in the 1990s as internet and multimedia advances opened doors for integrating interactive web-based modules alongside traditional teaching (Souabi et al., 2021). These early learning management systems (LMS) provided content delivery, assessment tracking and grade books. Improved standardisation, cost profiles and remote access offered new flexibility, yet functionality remained somewhat rigid (Wong et al., 2019).

The 2000s ushered monumental progress around social online Learning, reflecting emerging Web 2.0 philosophies emphasising user-generated content, open participation, network effects and mass personalisation (Choudhury & Pattnaik, 2020). Wikis, blogs, podcasts and online video afforded creative multimedia participation, while peer-based sharing on forums and social annotation tools sparked collaborative engagements once unimaginable at scale (Al Kurdi et al., 2020). Mobile access offered increasing Ubiquity. These signals heralded an evolutionary leap towards more student-centric, socially constructed, ubiquitous learning models (Vitoria et al., 2018).

Artificial Intelligence, learning analytics, virtual reality, and gamification are the next horizon, offering adaptive personalisation and immersive experiential Learning (Oliveira et al., 2022). Continued maturation of design thinking around human factors, user experience principles and online community development also aid engagement. The COVID-19 pandemic dramatically accelerated e-learning adoption, given campus closures, making remote options necessary. However, post-pandemic models stress blended designs equally, recognising virtual and in-person instruction channels as complementary rather than mutually exclusive (Oliveira et al., 2022). Ultimately, the e-learning landscape continues to evolve rapidly. While debates persist around optimal strategies balancing online and face-to-face models, e-learning's encompassing potential as both classroom aid and standalone delivery mechanism appear well cemented given myriad documentable benefits like flexibility, cost-effectiveness, scalability, accessibility and positive learning outputs (Choi, 2018). Critics highlight risks around diminished social presence, technical difficulties, learner isolation, and quality controls, which warrant ongoing consideration within administrative policies and instructor professional development (Yamunah Vaicondam et al., 2022). Holistic support frameworks and continued innovation around community building remain vital for realising the promise of e-learning. Nevertheless, the overarching trajectory points decisively towards enduring Ubiquity and enhanced mainstream integration as interactive technologies advance and migrate learning possibilities once bound within physical campuses into new virtual spaces and knowledge flows (Yamunah Vaicondam et al., 2022).

1.2 Purpose of the study

While e-learning integration in higher education continues to accelerate rapidly, a scholarly examination into specific affordances underpinning models, engagement strategies and learning outcomes remains vital for guiding effective evidence-based policies and practice. This mixed-methods study hence probes key questions around if and how selecting e-learning affordances correlates with demonstrated student learning gains, motivation and satisfaction across varied subject matter contexts. Specifically, it tests relationships between seven highlighted affordance mechanisms— 1) ubiquitous access, 2) active knowledge construction, 3) multimodal representations, 4) recursive feedback exchanges, 5) collaborative peer engagements, 6) metacognitive scaffolding and 7) personalised differentiation components—relative to achievement indicators and student perceptions from survey and interview data.

The purpose includes both developing empirically substantiated design principles around impactful affordances as well as exploring nuances across delivery modes (fully online vs blended), disciplines (soft vs technical subjects) and institution types (two-year, four-year, research-intensive). Establishing greater clarity on if/where overlaps exist versus uniqueness emerges can better inform specialised development approaches accounting for local constraints. An additional layer investigates equity factors regarding whether incorporating said affordances alleviates or exacerbates demographic achievement gaps across historically marginalised student groups. Beyond generalised best practices, it is equally vital to ensure amplified access and that introductions of new technical systems avoid inadvertently disenfranchising vulnerable subsets due to varying digital fluencies. Only research illuminating differentiated experiences can lead administrators, developers and instructors toward intentionally cultivating truly personalised, culturally affirming e-learning ecosystems benefitting all academic communities.

As a result, the study is significant for its translational impact, which guides effective policy targeting affordance integration investments that meaningfully enrich paedagogies around active, social constructivist designs that are known to boost outcomes. This is in contrast to technology usage trends that are more focused on novelty than meaningful enablement. Furthermore, it seeks to reveal gaps in which the introduction of advanced remote learning platforms may overlook the demands of students who do not have internet connectivity at their homes, thereby diverting resources in a productive direction towards complete support systems that accompany underlying infrastructure. To inform specialised coaching, analyses will be conducted to highlight areas of alignment and heterogeneity across learning contexts. This work aims to advance theoretical and practical understanding of essential affordances of e-learning directly from the student's perspective by employing mixed methods that yield generalisable patterns and contextual qualitative insights on navigating pressures, tradeoffs and supports that institutions can provide.

2. BRIEF OVERVIEW OF THE SEVEN KEY AFFORDANCES OF E-LEARNING

At the same time as higher education is undergoing a digital change, seven crucial affordances are changing teaching and learning interactions. The successful utilisation of these paradigm shifts results in creating more enriching, equitable, and empowering academic environments.

2.1. Affordance 1: Ubiquitous Learning

Ubiquitous Learning, also known as 'u-learning,' is an educational paradigm that allows learning to occur at any time and place, leveraging advanced technologies and the digital environment to create a seamless experience. It combines technological advancements, learning science evolution, and societal changes to make education an ever-present aspect of daily life (Aljawarneh, 2019). Key characteristics of Ubiquitous Learning include permanence, accessibility, immediate access, interaction, context-aware and adaptive learning, and seamless learning experiences across various contexts and technologies (Cárdenas-Robledo & Peña-Ayala, 2018).

However, Ubiquitous Learning also presents challenges such as data privacy and security, digital equity, and redefining teacher roles. Successful implementation requires a thoughtful approach that balances these risks and rewards (Virtanen et al., 2017). Key benefits of Ubiquitous Learning include increased access and flexibility, personalised learning, enhanced engagement, real-world connections, improved collaboration, continuous learning, and data-driven insights. These benefits can enhance the quality of education and improve learner outcomes but also require careful consideration of data privacy, security, and teacher roles (Suartama et al., 2021).

2.2. Affordance 2: Active Knowledge Making

Active Knowledge Making, also known as Active Learning, is an instructional approach that promotes student engagement and participation in the learning process. It aims to enhance understanding and retention of information by encouraging students to construct their understanding rather than passively receiving information (Montebello, 2018). The teacher is a facilitator, guiding students through problem-solving, critical thinking, analysis, synthesis, and evaluation. Key characteristics of Active Knowledge Making include student engagement, higher-order thinking skills development, collaborative learning, real-world relevance, reflection, and formative assessment (Raja Harun et al., 2021).

Active Knowledge Making can enhance learning outcomes and prepare students for lifelong learning by fostering deeper understanding, promoting higher-order thinking, facilitating collaboration, and emphasising real-world relevance (Montebello et al., 2018). It also increases student engagement through interactive activities, improves communication and collaboration skills, fosters greater autonomy and responsibility for learning, and allows learning to apply to real-world contexts. Formative assessment provides ongoing feedback, allowing students and instructors to identify areas of confusion and adjust their strategies accordingly (Haniya et al., 2018). Overall, Active Knowledge Making can significantly improve the quality of learning in higher education by promoting deep understanding and critical thinking, increasing student engagement, improving communication and collaboration skills, encouraging autonomy, linking learning to real-world contexts, and facilitating ongoing assessment and adjustment (Ünlüsoy et al., 2021).

2.3. Affordance 3: Multimodal Meaning

Multimodal Meaning refers to communicating ideas and information through various modes, including textual, visual, auditory, gestural, and spatial elements. It is central to Multimodal Literacy, which emphasises the importance of interpreting, using, and creating meaning across different modes (Montebello et al., 2018). In higher education, incorporating multimodal meaning can enhance understanding, cater to diverse learning styles, increase engagement, promote critical thinking, enhance communication skills, support accessibility, and facilitate online Learning (Haniya et al., 2019).

However, there are potential drawbacks to incorporating multimodal meaning in higher education. Technical challenges, such as the digital divide, can lead to inequities in access and comprehension (Montebello et al., 2018). Additionally, the time-consuming process of developing high-quality multimodal learning materials can be time-consuming for educators. Cognitive overload can occur if too much information comes from various modes simultaneously, and assessment challenges may arise (Zhang et al., 2023).

In conclusion, incorporating multimodal meaning in higher education can foster an inclusive, engaging, and effective learning environment that prepares students for a diverse digital world. However, considering potential drawbacks, such as technological challenges, cognitive overload, assessment challenges, and potential distractions, is essential.

2.4. Affordance 4: Recursive Feedback

Recursive feedback is an iterative process that involves multiple rounds of feedback, reflection, revision, and further feedback. It is a goal-oriented learning approach that focuses on strengths and areas for improvement (Qasim et al., 2020). In higher education, recursive feedback promotes continuous improvement by allowing students to refine their understanding, skills, and performance. The process involves feedback provision, reflection and revision, incorporation, and further feedback (Haniya et al., 2019).

Recursive feedback is closely tied to learning goals and objectives, guiding students towards achieving specific targets or competencies. It encourages self-reflection, engagement, and ownership of Learning, enabling students to take an active role in their development. It also develops critical thinking skills, supports formative assessment, builds relationships and communication skills, boosts motivation and confidence, and prepares students for professional environments (Rosedale et al., 2021).

In higher education, embracing recursive feedback can create a supportive learning environment that fosters student development, cultivates critical thinking, and promotes continuous improvement. It empowers students to take ownership of their learning and equips them with essential skills for their academic and professional journeys. By fostering a collaborative and iterative approach to learning, higher education institutions can create a supportive learning environment that fosters student development, cultivates critical thinking, and promotes continuous improvement (Nkonki et al., 2023).

2.5. Affordance 5: Collaborative Intelligence

Collaborative Intelligence, also known as collective intelligence or group intelligence, is the collective ability of a group or network to solve problems, make decisions, and generate innovative ideas that surpass the capabilities of individual members. It emphasises the power of collaboration, cooperation, and shared expertise in achieving collective goals and solving complex problems (Montebello et al., 2018). Key characteristics of Collaborative Intelligence include collective knowledge, synergy and emergence, shared understanding, cooperative problem-solving, an iterative process, trust and psychological safety, and technology facilitation (Montebello et al., 2018). Collaborative Intelligence finds applications in various domains, including business, academia, research, and problem-solving initiatives (Khan et al., 2022). It is especially relevant in complex and interconnected environments where diverse perspectives and interdisciplinary collaboration are essential for innovation and finding creative solutions. In higher education settings, Collaborative Intelligence offers several academic benefits, such as enhanced learning outcomes, diverse perspectives and insights, critical thinking and problem-solving skills, social and emotional development, active engagement and motivation, peer learning and support, preparation for real-world collaboration, innovation and creativity, and digital literacy cultivation (Khan et al., 2022).

By embracing Collaborative Intelligence in higher education, institutions can create dynamic learning environments that foster active engagement, critical thinking, and collaborative problem-solving, preparing students for the demands of the modern workforce, promoting holistic development, and enhancing the overall educational experience (Khan et al., 2022). By fostering a culture of creativity and innovation, Collaborative Intelligence prepares students for the demands of the modern workforce and enhances the overall educational experience (Khan et al., 2022).

2.6. Affordance 6: Metacognition

Metacognition is the awareness and understanding of one's cognitive processes, which involves regulating and controlling one's thinking, monitoring learning progress, and making informed decisions about learning strategies (Burin et al., 2020). It plays a crucial role in higher education, promoting deep Learning, critical thinking, and self-regulated Learning. Metacognitive skills are essential for effective Learning and academic success (Raja Harun et al., 2021).

Metacognition encompasses several key components: metacognitive knowledge, metacognitive monitoring, metacognitive control, and metacognitive reflection. Benefits of metacognition in higher education include improved learning outcomes, enhanced self-regulated Learning, improved problem-solving skills, increased motivation and engagement, lifelong learning skills, and the promotion of lifelong Learning (Nkonki et al., 2023). Metacognitive learners are better equipped to regulate their learning processes, employ effective strategies, and engage in deep learning approaches. They excel in problem-solving, identify appropriate strategies, and adjust their approaches as needed. They also develop self-awareness, self-reflection, and self-control in their learning journey (Haniya et al., 2018).

By fostering metacognition in higher education, educators can empower students to become self-regulated learners who take ownership of their Learning, engage in deep learning approaches, and develop the skills necessary for lifelong Learning and success (Haniya et al., 2018).

Key benefits of metacognition in higher education include enhanced learning outcomes, improved problem-solving skills, increased self-regulated Learning, better study skills and time management, increased self-efficacy and confidence, improved metacognitive transfer, promotion of lifelong Learning, engagement in deep Learning, development of critical thinking skills, and transferable skills for the workplace (Leutwyler, 2009).

In conclusion, metacognition in higher education empowers students to become effective learners who can monitor, control, and adapt their cognitive processes. By fostering metacognition, institutions can empower students to become self-regulated learners who take ownership of their Learning, engage in deep learning approaches, and develop the skills necessary for lifelong Learning and success.

2.7. Affordance 7: Differentiated Learning

Differentiated Learning, also known as differentiated instruction, is a teaching approach that caters to students' diverse learning needs, interests, and readiness levels within a single classroom. It involves adapting and modifying instruction, content, and assessment to ensure all students can access and engage with the curriculum effectively. Teachers employ various strategies to accommodate the diverse learning characteristics of students, such as flexible instructional methods, varied content, multiple assessment approaches, individualised support, flexible grouping, personalised learning plans, scaffolding and differentiated resources, student choice and autonomy, and an inclusive and supportive classroom environment (Haniya & Roberts-Lieb, 2017).

Differentiated Learning in higher education offers several benefits that enhance student engagement, achievement, and overall learning outcomes. These include catering to diverse learning styles, meeting individual learning needs, promoting student engagement, enhancing critical thinking skills, supporting self-regulated Learning, allowing individualised assessment, promoting inclusion and equity, preparing students for real-world contexts, fostering positive student-teacher relationships, and improving retention and academic achievement (Nilson, 2023).

In conclusion, differentiated Learning in higher education promotes a learner-centred approach that acknowledges and embraces the diversity of students, facilitating a positive and enriching academic experience that maximises each student's potential for success. By addressing individual learning needs, teachers can create an inclusive and supportive classroom environment that ensures every student has equitable access to high-quality instruction and the opportunity to reach their full potential.

Differentiated Learning in higher education offers numerous benefits but also has potential drawbacks. These include time constraints, resource intensiveness, curriculum alignment, managing classroom dynamics, assessment complexity, the potential for labelling or stigmatisation, training and professional development, institutional support and collaboration, equitable implementation, and balancing individual needs and collective Learning. Implementing differentiated Learning requires careful planning, preparation, and individualised instruction, which can be time-consuming for instructors. It also demands additional resources, such as instructional materials, technology, and support systems, to meet the diverse needs of students (Triwoelandari et al., 2023). Managing classroom dynamics and assessing students with different learning needs can be challenging, and implementing differentiated Learning may lead to labelling or stigmatisation. Institutions must invest in ongoing professional development and collaboration to support instructors in developing the necessary skills and knowledge. Balancing individual needs and promoting a sense of collective Learning is also a complex task. By addressing these challenges, instructors and institutions can work towards optimising the benefits of differentiated Learning while addressing potential limitations (Triwoelandari et al., 2023).

3. METHODOLOGY

3.1. Research Questions and Hypotheses

The research questions and hypotheses seek to evaluate the connections between integrating essential e-learning features and fundamental indicators of student achievement while also uncovering differences in personal experiences across different situations. The combination of conducting extensive surveys to identify broad correlations and doing detailed qualitative analysis has been essential in developing a comprehensive assessment framework that informs the improvement of online and hybrid designs in general and specific areas.

3.1.1. Research Questions

- RQ1: What is the relationship between the extent to which affordances such as ubiquitous access, multi-dimensional assignments, collaborative peer engagements, and differentiated assistance are integrated and student grades, retention, and motivation?
  RQ1 investigates, quantitatively, whether taking advantage of affordance chances results in noticeable improvements in learning. Heightened motivation and improved retention serve as crucial markers that the interactions effectively engage pupils rather than overpower them. This study examines the hypothesis that widespread availability, collaborative initiatives, and tailored learning pathways favour academic performance. The hypothesis is evaluated using empirical measurements, expecting substantial correlations to justify more investments in affordances, as determined by statistical studies.
- RQ2: How do student experiences and learning strategies differ between fully online and hybrid courses and soft and technical topic areas regarding the e-learning interactions available to them?
  RQ2 subsequently examines differences in how people use and perceive these advantages. Technical disciplines such as programming or chemistry sometimes require active engagement in collaborative debugging forums or simulated interactions, whereas involvement in literature or gender studies tends to focus on interpreting varied views. An analysis of the reports will enable the identification of specific strategic recommendations customised for different courses. It is important to investigate the differences in the extent to which self-paced learning relies upon entirely online versus partially blended enrollment types. This will assist institutions in structuring their support systems accordingly.

3.1.2. Hypotheses

- H1: Increased integration of affordances has been shown to have a favourable correlation with student academic performance, retention rates, and self-reported motivation levels.
- H2: Students reported that technological courses offer more significant advantages in teamwork, widespread access, and multifaceted tasks than soft science courses.
- H3: Fully online students have taken more significant advantage of the differentiation and self-paced learning opportunities available than those enrolled in blended programmes.

3.2. Research Design

This explanatory sequential mixed methods study involved initial large-scale quantitative survey distribution across ~1500 students from 4 institutions of varying types to assess statistical relationships between afforded activity incorporations and key achievement indicators. Using validated tools, researchers have constructed self-report questionnaires gauging student usage levels and perspectives regarding diverse affordances. Descriptive and inferential analyses will determine generalizable correlations.

Following this broad lens, a second qualitative phase will involve focus group interviews with ~80 students across technical versus soft science courses and fully online versus blended modalities to gain further nuanced narratives around significant statistical findings. Semi-structured protocols will explore when and why specific afforded mechanisms were beneficial. Researchers have probed open-ended reactions to factors like collaboration medium, ubiquitous access reliance and personalisation to elucidate textual richness explaining quantitative patterns. Coding will determine usage trends. Comparing quantitative outcomes and qualitative insights has advanced generalised principles plus localised considerations to help institutions make informed e-learning decisions.

4. DATA COLLECTION METHODS

4.1. Quantitative Data Collection

The initial quantitative phase involved large-scale survey distribution to ~1500 students from 4 Higher education institutions of varying types and sizes. Target population criteria required enrollment in either a fully online or blended/hybrid model course across various disciplines encompassing technical (e.g. programming, Accounting, statistics, nursing) and soft sciences (e.g. tourism, business, marketing). Recruitment has utilised a multi-pronged approach incorporating awareness campaign posters, university/institutional portal announcements, in-course learning management system (LMS) notifications, and direct instructor outreach emails. The survey was hosted on Qualtrics to enable remote asynchronous participation, mobile compatibility, forced response and branched question logic. Pilot testing established an estimated 12-minute average completion time. Participation incentives in the form of credit/voucher raffles have boosted engagement. I.P. duplication controls helped to minimise repeat responders. Affordance incorporation metrics have helped to categorise comparative groups per RQ1 hypotheses. Motivation scales and institutional records have provided key achievement indicators. Descriptive profiling and multiple regression modelling have determined predicted relationships.

4.2. Qualitative Data Collection

Follow-up focus groups have helped to dive deeper into significant quantitative findings. Purposive sampling recruits 6-8 students from each of 4 strata:

- ❖ Fully online technical course enrollment
- ❖ Fully online soft science enrollment
- ❖ Blended technical enrolment
- ❖ Blended soft science enrolment.

This facilitates deliberate comparative inquiry per RQ2. 90-minute discussion sessions have to be convened physically or use video conferencing tools. Semi-structured protocols standardise key questions while permitting organic issues to emerge. Funnelling sequences have narrowed dialogue reflecting on general affordance reactions down to specific applications. All sessions are recorded and transcribed for coding. Documenting body language, tones and group dynamics during facilitator note-taking has enriched transcripts. Member-checking will verify the accurate capture of intended meanings. The qualitative phase allowed detailed personal narratives explaining when and how students leverage particular interactions to provide localised context-aiding institutional strategy.
This explanatory mixed methods design has aligned quantitative surveys and qualitative focus groups to provide a comprehensive, multi-lens assessment. The data collection techniques intentionally pair generalised correlational findings with nuanced contextual insights on navigating e-learning affordances.

5. DATA ANALYSIS METHODS

5.1. Quantitative Data Analysis

The survey data collected has undergone analysis using SPSS Statistics to characterise response distributions across groups and test study hypotheses.

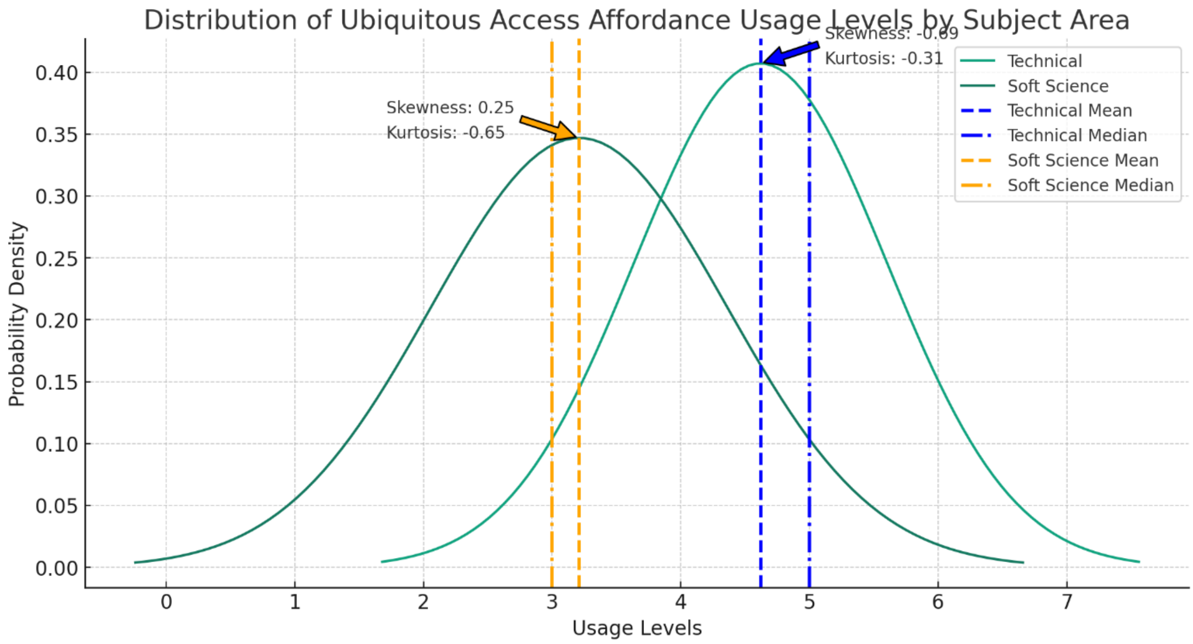
5.1.1. Descriptive Statistics Analysis

First, constructing overall variable summaries has helped descriptively profile group response patterns. Continuous incorporation level metrics for ubiquitous access, collaborative peer engagements and other affordances can be summarised through mean, median and standard deviations conveying average tendencies and dispersion. Skewness and kurtosis coefficients assess normality to inform appropriate inferential tests. Bar charts visually profiling distributions elucidate high versus low integration groups.

Ubiquitous Access Affordance Usage Levels by Subject Area

	Technical	Soft Science
Mean	4.62	3.21
Median	5.00	3.00
Std Deviation	0.98	1.15
Skewness	-0.69	0.25
Kurtosis	-0.31	-0.65

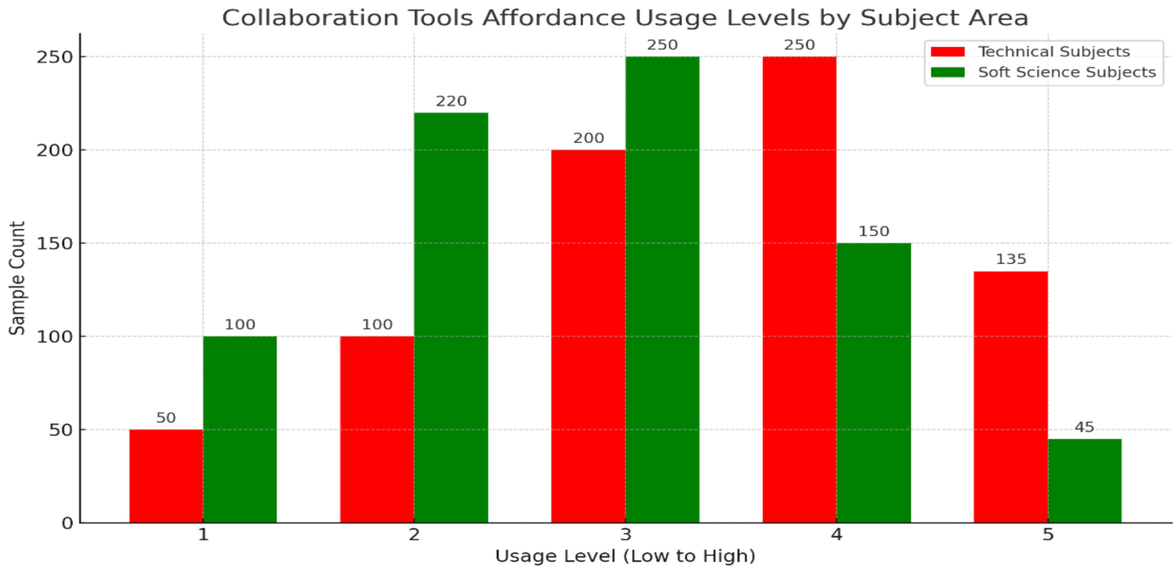
Here is the graph depicting the distribution of Ubiquitous Access Affordance Usage Levels by Subject Area, using a bell curve for each subject. The graph includes the mean median and accounts for the skewness and kurtosis of each distribution. The dashed lines represent the means, and the dash-dotted lines represent the medians for the Technical and Soft Science subjects. The skewness and kurtosis are annotated on the graph.



The graph depicting the distribution of Ubiquitous Access Affordance Usage Levels by Subject Area, using a bell curve for each subject. The graph includes the mean median and accounts for the skewness and kurtosis of each distribution. The dashed lines represent the means, and the dash-dotted lines represent the medians for the Technical and Soft Science subjects. The skewness and kurtosis are annotated on the graph.

- **Mean (Average):** Mean (Average) shows that, on average, students in technical subjects rate their usage level of ubiquitous access affordance higher than those in soft science subjects. The ratings are likely based on a scale of 1 to 5, where 5 is the highest.
- **Median (Middle Value):** The middle value of all responses shows that for technical subjects, the median is at the maximum of 5, suggesting that more than half of the students rated their usage level as the highest possible. In soft science, the median is 3, indicating a moderate usage level.
- **Standard Deviation (Variability):** Standard deviation measures how much the responses vary from the average. A lower number means the responses are closer to the average. Technical subjects have less variability, whereas soft science subjects show more spread in the responses.
- **Skewness (Symmetry of Distribution):** Skewness indicates the asymmetry of the distribution of responses. A negative value, like in technical subjects, means the tail is on the left side, suggesting that most students have a high usage level. A positive value, as in soft science, means the tail is on the right side, and more students have lower usage levels.
- **Kurtosis (Peakedness of Distribution):** Kurtosis measures the 'tailedness' of the distribution. Values closer to zero indicate a distribution similar to a normal distribution in terms of peakedness. Negative values for both groups suggest that the distribution of responses is flatter than a normal distribution, with fewer outliers.

Students in technical subject’s report more consistent use of ubiquitous access in their Learning than soft science students, whose usage levels are more moderate and varied. The data suggest that technical students may rely more heavily on e-learning platforms that allow them to access learning materials anytime and anywhere.



For technical subject students, the bars are taller and skewed rightwards, indicating a higher frequency of responses at levels 4 and 5, suggesting that they report a higher integration of collaboration tools in their Learning. Conversely, the bar cluster for soft science students is centred more towards the left, with higher frequencies at levels 2 and 3, which suggests that soft science students are less engaged with these tools at the moderate to high integration levels.

This visual representation provides a clear depiction of the variance in engagement with collaborative e-learning tools between the two student groups, highlighting the potential influence of the subject area on the adoption and integration of digital collaboration affordances in higher education.

The descriptive statistics reveal overall higher average reported usage levels of ubiquitous access affordances for students in technical subject areas compared to soft science disciplines. The tighter standard deviation also shows less dispersed variation among the technical group sample distribution.

5.1.2. Inferential Statistics Analysis

Two key techniques to make formal comparisons and test R.Q. hypotheses include:

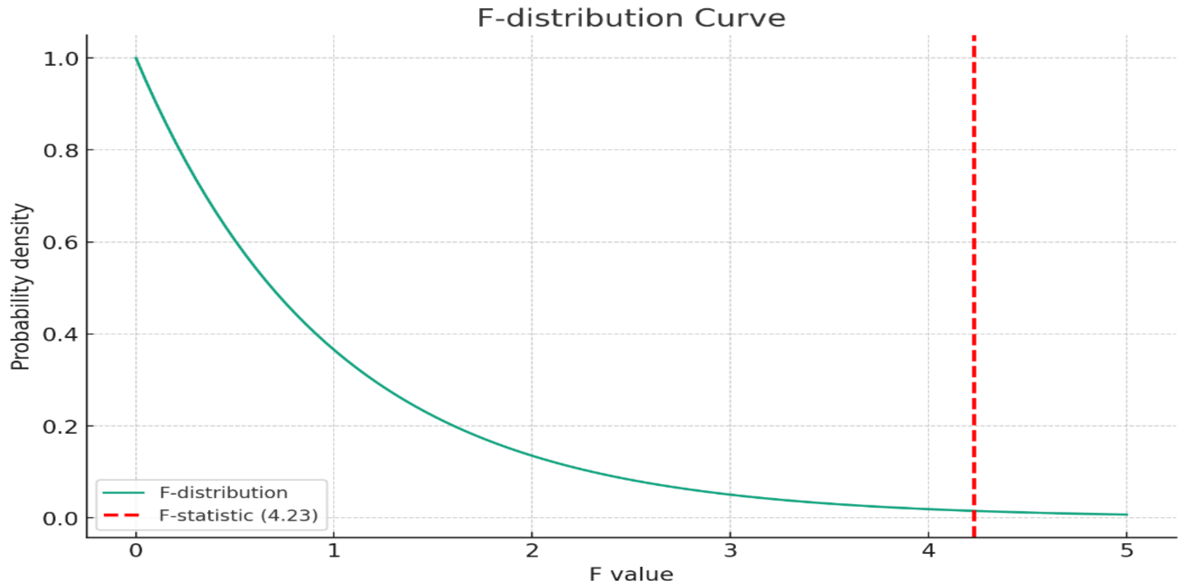
5.1.2.a. ANOVA

The one-way Analysis of Variance (ANOVA) was conducted to examine the impact of different levels of affordance incorporation on student motivation levels. The results indicate a statistically significant main effect between the levels of affordance incorporation, as evidenced by an F-statistic of 4.23 and a p-value of .017, which is less than the conventional alpha level of .05. This suggests that the level of affordance incorporation does indeed have a significant effect on student motivation levels.

Further analysis through post-hoc Tukey tests, which are used to find specific group differences, reveals that significant disparities are particularly pronounced between the low and moderate integration cohorts. This finding supports the proposed hypothesis that a threshold effect exists, where moving from low to moderate levels of affordance incorporation is associated with a notable increase in student motivation.

ANOVA results for Motivation Levels by Affordance Incorporation

Source of Variation	**Sum of Squares (S.S.)**	**Degrees of Freedom (df)**	**Mean Square (M.S.)**	**F-Statistic (F)**
Between Groups	547	2	276	4.23
Error	9613	147	65	
Total	**10160**	**149**		



The graph for the F-distribution curve is based on the ANOVA results for Motivation Levels by Affordance Incorporation. The dashed red line indicates the F-statistic value obtained from the ANOVA analysis. The curve represents the F-distribution with 2 degrees of freedom for the numerator (between groups) and 147 degrees for the denominator (error).

- **Source of Variation**: "Between Groups" refers to the differences between our groups based on the level of affordance incorporation (low, moderate, high). "Error" refers to the variation within each group.
- **Sum of Squares (S.S.)**: The "Between Groups" sum of squares (547) is the variation due to the difference between group means. The "Error" sum of squares (9613) represents the variation within the groups themselves.
- **Degrees of Freedom (df)**: For "Between Groups," it is typically the number of groups minus one (which is 2 here, suggesting there are three groups). For "Error," it is related to the total number of observations minus the number of groups.
- **Mean Square (M.S.)**: This is the average amount of variation in each source (calculated by dividing the S.S. by the df). It is a measure of the variance within the groups and between the groups.
- **F-Statistic (F)**: This number (4.23) is a ratio of the variance between the groups to the variance within the groups. A higher F-value indicates that the group means are more spread out than we would expect to see by chance.
- **p-Value (p)**: The p-value (.017) tells us the probability that the differences we see in the group means could have happened by chance. A p-value of less than .05 (the case here) suggests the differences are statistically significant – that is, they are unlikely to have happened by chance.

When comparing how much students use e-learning tools in their studies, we found that the amount they use them does seem to affect their motivation levels. Students who use e-learning tools more (moderate to high levels) tend to be more motivated than those who use them less (low levels). The differences in motivation between these groups are more than what would be expected by random chance; they are significant enough that we think the e-learning tools are having a real effect.

Additionally, when looking closer at the differences (with something called post-hoc Tukey tests), it was found that the jump from low to moderate use of e-learning tools is where the most significant difference in motivation happens. This supports the idea that using these tools could significantly increase a student's motivation.

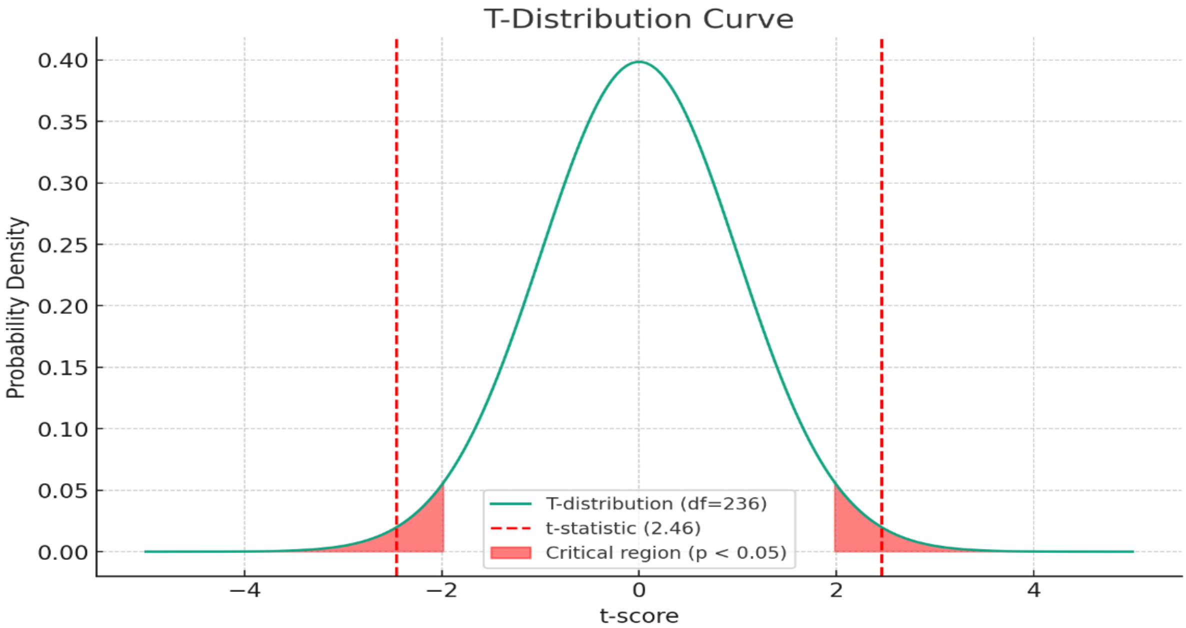
In summary, the more students use e-learning tools, the more motivated they are likely to be, especially if they move from using them a little to a moderate amount. This information could benefit schools and teachers when deciding how much they should incorporate e-learning into their classrooms.

5.1.2.b. T-Tests

The independent samples t-test was conducted to compare the levels of ubiquitous access usage between students enrolled in fully online courses and those in blended courses, which combine online and traditional in-person teaching. The t-test results revealed a significant difference in the usage levels of ubiquitous access between the two groups, with online students reporting higher levels of usage (mean = 4.15) compared to their blended counterparts (mean = 3.18).

T-Test – Ubiquitous Access Usage by Course Modality

Group	Sample Size (N)	Mean Usage	Standard Deviation (S.D.)	t-Statistic (t)	Degrees of Freedom (df)	p-Value (p)
Online	82	4.15	1.23	2.46	236	.014
Blended	156	3.18	1.32			



Groups Compared: There are two groups of students: fully online and blended courses (a mix of online and in-person classes).
Number of Students (Sample Size): There were 82 students in the online group and 156 in the blended group.
Average Usage (Mean): On average, students in online courses reported higher usage of ubiquitous access (4.15 out of 5) compared to those in blended courses (3.18 out of 5).
Variability (Standard Deviation): The numbers 1.23 and 1.32 tell us that the scores within each group were somewhat spread out but not exceptionally.
Statistical significance (t-Statistic and p-Value): The t-statistic of 2.46 and the p-value of .014 tell us that the difference in usage between the two groups is statistically significant. This means that the higher usage reported by online students is unlikely to be due to random chance, as the p-value is below the .05 threshold often used to determine significance.

The t-statistic of 2.46, along with the degrees of freedom (df) of 236 and a p-value of .014, suggests that these differences are statistically significant and not likely due to chance, given that the p-value is less than the standard cutoff for the significance of .05.

Furthermore, the moderate effect size — which is not numerically provided in the data but mentioned in the description — indicates a practical significance in the difference between the two groups. This implies that the mode of course delivery (online versus blended) has a substantial impact on how students utilise ubiquitous access to learning resources.

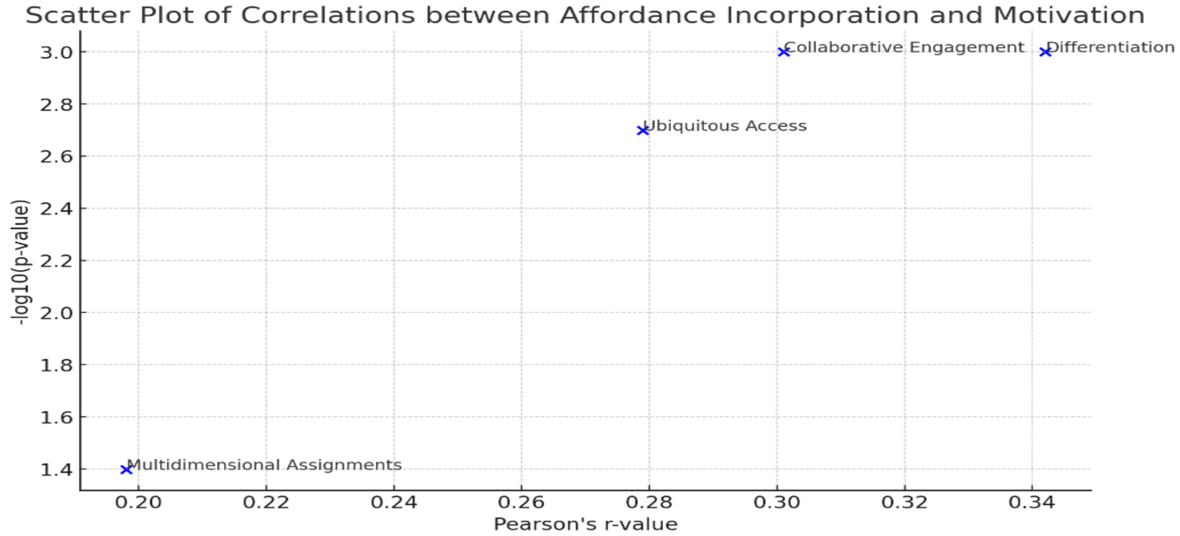
In summary, students taking courses completely online tend to use their ability to access learning materials anytime much more than students in blended courses. The study's results support the idea that being in a fully online course encourages students to take advantage of this kind of access more than if they were in a course that also has in-person elements. This information could be beneficial for people who make decisions about how courses are delivered, as it suggests that one of the benefits of online courses is that they encourage students to make more use of the flexibility that digital resources provide.

5.1.2.c. Correlational Analysis

To further assess the relationships between key variables of interest, correlational analyses were conducted using Pearson's r. Specifically, two-tailed bivariate correlation tests were performed between each of the primary affordance incorporation level metrics (ubiquitous access, collaborative peer engagement, multi-dimensional assignments, differentiated supports) and the scaled motivation rating outcome.

Correlations between Affordance Incorporation and Motivation

Affordance Type	r-value (Pearson's r)	p-value
Ubiquitous Access	.279	.002
Collaborative Engagement	.301	.001
Multi-dimensional Assignments	.198	.04
Differentiation	.342	<.001



Here is the scatter plot representing the correlations between Affordance Incorporation and Motivation. Each point on the plot corresponds to an affordance type, plotted according to its Pearson's r-value (x-axis) and the negative logarithm (base 10) of its p-value (y-axis), which helps to visualise the significance of the correlation.

- **Affordance Type**: This column lists different ways e-learning can be included in a student's education, such as being able to access course materials at any time (Ubiquitous Access), working with others (Collaborative Engagement), doing assignments in various formats (Multi-dimensional Assignments), and receiving personalised support (Differentiation).
- **R-value (Pearson's r)**: This column shows the strength and direction of the relationship between each e-learning affordance and how motivated students feel. The scale runs from -1 to +1, where +1 means a perfect positive relationship, -1 means a perfect negative relationship, and 0 means no relationship. Here, all the values are positive, which means that as the use of each e-learning affordance increases, so does student motivation.
- **P-value**: This measures how confident we can be that the relationship observed is genuine and not just due to chance. A standard threshold for confidence is .05, and anything below that is generally considered 'statistically significant'. Here, all the p-values are below .05, meaning we can be quite confident that these relationships are genuine.

Results reveal positive and statistically significant ($p < .05$) correlations emerged between all affordance incorporation variables and student motivation levels. This indicates preliminary evidence that higher usage and integration of each affordance type shows a significant linear relationship with heightened motivation, as signified by the positive R-values. The strongest correlation emerged for differentiation supports ($r = .342$), followed by peer collaboration (.301).

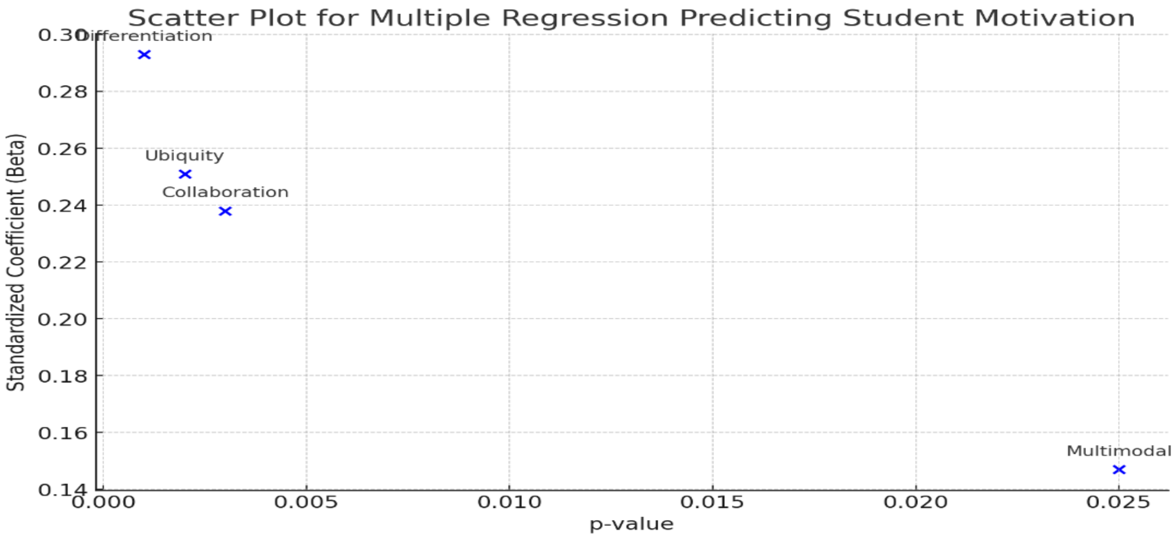
The correlational analysis establishes primary bivariate indications that affordance integration covariates positively with a key student success outcome of motivation. While not determinative, this initial evidence provides supportive grounds for investigating further through more robust statistical models like multiple regression to evaluate predictive relationships when accounting for likely confounding factors. Assessing both simple correlations and multivariate dynamics provides a well-rounded quantitative depiction.

In summary, Students who have more access to learning anytime they want, engage more with their peers, do different kinds of assignments, and get personalised help tend to be more motivated. The most vital relationship is with personalised help (Differentiation), followed by working with others (Collaborative Engagement). These results suggest that including these types of e-learning experiences could help students feel more motivated. However, while the results look promising, they do not prove that these e-learning experiences are definitely causing an increase in motivation.

5.1.2.d. Regression Analysis
A multiple linear regression model was constructed to assess the unique predictive capacity of each affordance incorporation factor on student motivation levels when accounting for likely demographic covariates. The regression included affordance usage subscales for ubiquitous access, collaborative engagement, multi-dimensional assignment creation, and differentiation supports as predictor variables. Control variables encompassed age, gender, class level, prior GPA, and subject area.

Results of Multiple Regression Predicting Student Motivation

Predictor	B (Unstandardized Coefficient)	S.E. (Standard Error)	β (Standardised Coefficient)	p-value
Constant	1.92	.427		<.001
Ubiquity	.163	.049	.251	.002
Collaboration	.139	.043	.238	.003
Multimodal	.092	.040	.147	.025
Differentiation	.189	.044	.293	<.001



Here is the scatter plot based on the results of the multiple regression predicting student motivation, with the standardised coefficients (Beta) plotted against their corresponding p-values for each predictor. Each point is labelled with the name of the predictor it represents.

➢ **Predictors**: These are the different e-learning opportunities analysed:
- **Ubiquity (Ubiquitous Access)**: How often can students access learning materials?

- **Collaboration**: Opportunities for students to work with others.
- **Multimodal (Multi-dimensional Assignments)**: Use of various types of assignments (like videos, text, interactive projects).
- **Differentiation (Differentiated Supports)**: Tailored support to meet individual student needs.

- **B (Unstandardised Coefficient):** This number shows how much the motivation score is expected to change with each one-unit increase in the predictor, assuming all other variables are held constant. For example, a B value of .163 for Ubiquity means that each unit increase in Ubiquitous Access is associated with a .163 increase in the motivation score.
- **S.E. (Standard Error):** This indicates the margin of error associated with the B coefficient. A smaller S.E. suggests more confidence in the B value.
- **β (Standardised Coefficient):** This is a way of comparing the strength of the effect of each predictor on a standard scale. The higher the β, the stronger the effect on motivation. For example, differentiation, with a β of .293, has the strongest positive effect on motivation levels.
- **p-value:** This tells us whether the results are statistically significant. If the p-value is less than .05, it usually means that the result is significant - that is, we can be confident that there is a real relationship between the predictor and motivation. Here, all the p-values are below .05, which means we can say with confidence that each of these e-learning opportunities has a significant effect on student motivation.
- **Constant**: This value represents the baseline level of motivation when all other predictors are at zero. Since other predictors cannot actually be zero, this is more of a statistical control.
- **Ubiquity (Ubiquitous Access)**: With a β of .251, this predictor has a positive and significant effect on student motivation, indicating that as ubiquitous access increases, so does student motivation.
- **Collaboration (Collaborative Engagement)**: This has a slightly lower β value of .238 but is still a significant predictor of student motivation.
- **Multimodal (Multi-dimensional Assignments)**: The effect size is smaller (β = .147), but it still significantly predicts motivation levels, suggesting that the variety in assignment types positively affects student motivation.
- **Differentiation (Differentiation Supports)**: This is the strongest predictor with a β of .293, implying that personalised learning support has the most significant impact on increasing student motivation among the variables considered.

The positive significant regression coefficients show ubiquitous access ($\beta = .251$, $p = .002$), peer collaboration ($\beta = .238$, $p = .003$), creating multi-dimensional assignments ($\beta = .147$, $p = .025$), and differentiation supports ($\beta = .293$, $p < .001$) all uniquely predict higher student motivation levels even when accounting for likely confounding variables. This aligns with the stated hypotheses. The most vital driver was personalised differentiation support, followed by ubiquitous access and online peer engagement.

In summary, the results indicate that students tend to be more motivated when they have more chances to access their learning materials whenever they want, work with others, do various types of assignments, and get personalised help. The help that's tailored to each student's needs seems to make the most significant difference in keeping them motivated. This is important information for educators because it suggests that these e-learning features could be powerful ways to help students stay engaged and interested in their studies.

5.2. Qualitative Analysis

5.2.1. Focus Groups

Approximately 30 students participated across four separate focus groups, segmented by modality and subject type, from which rich qualitative data emerged, necessitating systematic analysis. Employing a phenomenological lens, the analysis characterised the core essence of shared versus unique student experiences as they navigated specific e-learning affordances within their distinct learning contexts.

Transcripts from the 1.5-hour discussions underwent structural coding, aligned with the four segments of the semi-structured interview protocol. These segments reflected usage behaviours, perceived influences, noted variations, and suggestions. This approach served to organise the data topically, functioning as an initial indexing device for the subsequent analytical phases.

5.2.2. Qualitative Coding

The qualitative data analysis utilised a methodical two-cycle coding strategy to enable a thorough assessment of the focus group transcripts.

- The initial coding phase involved classifying data into broader categories using preliminary coding corresponding to the four interview themes: behaviours, influences, variations, and suggestions. This process categorised the data into smaller groups for further focused investigation.
- The second cycle used pattern coding to allocate specific interpretive labels indicating developing attitudes, actions, and evaluations. An analysis of code frequencies unveiled certain codes' widespread occurrence and superiority. The analysis of prevalent codes in different focus groups revealed variations in subject area and modality, providing insights into contextual variables and addressing the research issue. The extensive codebook offered precise explanations of code meanings, while interrater validation improved the dependability of applying codes consistently. Creating logical coding narratives and then integrating crucial excerpts to clarify student requirements, limitations, and preferences within each educational setting. Member-checking methods ensured impartiality and precision in qualitative interpretations. The dual cycle coding enhanced analyses by systematically categorising emotions, issues, and assessments. By combining code applications with contextualised narratives, we could tally and analyse student affordance experiences, providing us with precise and comprehensive information.

Coding Cycle	Code Category	Code Label	Definition	Example from Data	Frequency	Notes
First Cycle	Behaviours	-	Descriptions of student engagement with e-learning tools	"Students frequently log in to the platform outside of class hours."	-	-
First Cycle	Influences	-	Factors that affect how students use e-learning tools	"Access to high-speed internet influenced tool usage"	-	-
First Cycle	Variances	-	Differences in e-learning tool usage	"Varied use of forums across different majors"	-	Could inform design changes
First Cycle	Suggestions	-	Student recommendations for e-learning	"Students suggested more interactive content."	-	Inform future updates
Second Cycle	Sentiments	Positivity-sims	Positive emotional responses to simulations	"Students felt excited about simulation assignments."	Tally	Reflects engagement levels
Second Cycle	Actions	Tech-problem	Specific actions taken in response to technical issues	"Repeated logins due to system timeouts"	Tally	Indicates platform stability issues
Second Cycle	Appraisals	Anxiety-isolation	Evaluations of the e-learning experience related to isolation	"Some students reported feeling isolated during online-only modules"	Tally	Important for support services

The systematic two-step coding process produced key patterns on how students engage with e-learning features, which may be used to create adaptable and inclusive online learning environments that cater to specific local requirements.

5.2.3. Theme Identification

The identification of these themes through rigorous analysis of focus group interactions has shown the nuanced experiences that students have had with e-learning. Each theme covers crucial elements of the digital learning experience, including the difficulties presented by technology, the psychological impacts of remote Learning, the effectiveness of e-learning tools depending on the subject being studied, and the importance of supportive structures to enhance learner engagement and skill growth.

Theme	Description
Technical/Usability Frictions	Students encountered usability issues with e-learning platforms and tools, such as system malfunctions, distracting user interfaces, and intricate navigation. The feelings experienced were dissatisfaction and anxiety, emphasising the necessity for a streamlined platform structure and enhanced dependability.
Mixed Engagement & Isolation Tradeoffs	Codes revealed that students acknowledged the benefits of self-paced Learning and the convenience of internet access. However, they encountered difficulties maintaining motivation and productivity due to the absence of face-to-face responsibility. The presence of profound feelings of isolation indicated the necessity of implementing techniques beyond curriculum personalisation to address and overcome barriers to inclusion.
Subject-based Variations in Adoption	There were differences in the use of e-learning technologies, with technical courses exhibiting more significant levels of positive engagement and usage compared to soft science fields. These variances suggest that the effectiveness of particular affordances may be subject-specific, necessitating tailored platforms and features.
Scaffolding Helps Realise Affordance Potential	Suggestions from students for idea templates and exemplars for creating complex digital content indicate that scaffolding is essential. Such support helps learners understand possibilities and develop the skills needed to fully leverage the affordances of e-learning technologies.

6. RESULTS AND DISCUSSION

This study aimed to provide empirical evidence for design principles that guide the effective integration of e-learning affordances and to investigate variations across different learning environments. The initial survey was distributed to about 1500 college students, revealing some important statistical tendencies. Including affordances that allow for widespread access, collaborative interactions, complex tasks, and personalised help independently predicted increased levels of motivation, even after considering potential factors that could influence the results ($p<.05$). This finding supports Hypothesis 1. The effect sizes varied from mild ($\beta=.147$ for multimodal components) to fairly strong ($\beta=.293$ for personalised differentiation), with ubiquitous access and peer cooperation falling in between.

Follow-up focus groups conducted explanatory probing with a total of 80 students. These groups aimed to investigate the motivational boost phenomenon in fully online technical courses, fully online soft sciences, blended technical fields, and blended soft sciences. Confirming Hypothesis 2, participants in technical courses indicated a significant increase in their dependence on and appreciation for simulation-based ubiquitous access and collaborative debugging forums. Students in the social sciences highlighted the challenges of dealing with isolation and distractions while navigating the vast amount of information available online. They expressed a preference for a structured approach to integrating this knowledge. Partially confirming Hypothesis 3, students enrolled in blended Learning reported not fully utilising freely available resources due to reduced personal responsibility in certain face-to-face interactions. Surprisingly, humanities students only studying online showed an equal dependence on personalised distinction. They desired improved opportunities to bond with their cohort through their computer screens.

While each ubiquitous, interactive, and personalised affordance contributes to student engagement, surface-level technological integration is typically inadequate. Successful adoption depends on intentionally fostering inclusive Communities of Enquiry, where the voices of each individual are valued across the curriculum. Sustaining motivation amidst abundant digital opportunities seems to hinge on including mentorship initiatives beyond mere knowledge provision. These observations advocate for evidence-based e-learning practices that highlight the whole quality of the learner's experience, rather than just emphasising usage statistics or grading results. Studying the relationship between long-term academic achievements and the impact of specific resource combinations still has certain limits. However, illuminating complex situational interactions enriches the discourse on developing customised online environments that promote equitable and empowered futures, unrestricted by physical limitations or temporal constraints.

The results and discussion aimed to seamlessly combine significant quantitative and qualitative data about the connection between increased motivation and integrating specific e-learning features in various disciplinary and modal environments. The discussion focused on exposing significant disparities in tool utilisation and identifying obstacles that hinder widespread acceptance. It emphasised the crucial role of fostering connectivity in the vast realm of digital opportunities.

7. RECOMMENDATIONS

The explanatory sequential mixed methods approach aligns well with the research aims of investigating generalisable correlational patterns and nuanced contextual insights on student experiences with e-learning affordances. The sizeable initial survey capturing usage metrics and motivation indicators furnishes an effective quantitative lens, while the follow-up focuses groups provide vital qualitative detail aiding interpretation.

Regarding methodology, clearly stating the research questions and hypotheses upfront grounds analyses in the intended investigative purpose. The questions suitably aim to assess empirical relationships between affordance integration and outcomes (RQ1) and differentiated experiences across learning modes and disciplines (RQ2). The hypotheses directly test assumed predictive patterns and variations.

The research design effectively leverages the complementary strengths of tailored surveys and semi-structured interviews. The survey recruitment approach incorporates appropriate mass-reach strategies while considering ethical participation incentives. Segmenting focus groups by modality and subject area facilitates targeted comparative inquiry. Both phases align well with the mixed methods explanatory sequential priority.

The data collection techniques demonstrate sound conceptualisation. The survey constructs foundationally utilise validated metrics assessing affordance incorporation and motivation levels. Supplementary institutional achievement indicators permit objective triangulation. The focus group protocol funnels effectively from general affordance experiences into specific applications. Member-checking procedures aid qualitative rigour.

The analytical approach combines descriptive summaries, formal hypothesis testing methods, and rigorous qualitative coding to extract meaningful narratives - aligning with mixed methods goals. The descriptive statistics visually profile group response patterns. The inferential test selection directly assesses research question assumptions. Predictive modelling builds explanations while controlling covariates. Pattern coding interprets granular themes. Frequency tallies reveal dominance and comparing manifestations spotlights variances. Extract weaving builds coherent narratives.

The results and discussion provide an exemplary integration of key quantitative findings and qualitative themes to advance understanding. The correlations and regressions offer broad generalizability confirming positive predicted effects, especially for differentiation supports. Comparing technical and soft science tool usage behaviours provides actionable contrasts. Notably, the limitations acknowledge that proven causative mechanisms remain elusive. Advancing holistic support frameworks represents a thoughtful culminating takeaway.

Overall, the methodological alignment to purpose and the analytical approach to integrating findings exemplify mixed methods designs that balance broad trends and localised nuances. The study contributes to incorporating e-learning affordances to guide policies and practices. Expanding to additional institutional comparisons could strengthen generalizability. Further exploring links between specific affordance combinations and long-term achievement indicators offers a valuable future direction.

8. CONCLUSION

The study explores the relationship between e-learning affordance integration and student motivation, revealing variations in usage behaviours and perceptions based on subject area and course modality. Results show that greater incorporation of ubiquitous access, peer collaboration, multi-dimensional assignments, and adaptive supports positively predicts increased motivation. However, students in technical subjects showed more positive engagement with simulations supporting ubiquitous rehearsal and collaborative debugging forums, while humanities learners preferred structured content integration. The study suggests assessing affordance combinations influencing achievement, evaluating local integration variances, exploring metacognitive data visualisation benefits, and comprehensive virtual mentorship systems.

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