LA TROBE UNIVERSITY

Deciphering the Impact of Hybrid Teaching: Delving into the Crossroads of Intrinsic and Extrinsic Student Motivations

1 TABLE OF CONTENTS

2 ABSTRACT

This study examines the role of hybrid teaching, a blend of online and traditional classroom instruction, on student motivation. Two primary forms of motivation are considered: intrinsic, arising from a student's personal interest, and extrinsic, influenced by external rewards. The Intrinsic Motivation Inventory (IMI) was employed to gauge these motivations. The research also touches upon the potential challenges of online learning, underscoring the relevance of understanding student motivation in a hybrid setting. The research predominantly focuses on the comprehension of statistics by first-year university students, encompassing a sample of 126 participants from a health sciences course. In essence, the findings emphasize the need to account for student motivation when adopting hybrid teaching approaches, offering insights beneficial for educators aiming to refine the learning process. Notably, no significant variance in student motivation was observed when comparing hybrid teaching with solely online methods.

Keywords: *Hybrid Teaching, Intrinsic Motivation, Extrinsic Motivation, Intrinsic Motivation Inventory (IMI), Statistical Significance*

3 INTRODUCTION

Education has always been a crucial part of our lives, helping us gain skills and knowledge. Over the years, the way learning occurs has evolved. While we once relied heavily on classrooms and books, the rise of technology has introduced online learning as a significant player. This shift became even more pronounced during the global pandemic, emphasizing the importance of online platforms in keeping education going.

A central question arises from this shift: How does online learning affect a student's desire to learn? Generally, there are two main reasons why students learn. Some are driven by a genuine interest in the subject, known as intrinsic motivation. Others are motivated by external factors like getting good grades, known as extrinsic motivation.

One such method is "hybrid teaching," which merges the benefits of both online and traditional classroom instruction. To delve deeper into this concept, it's essential to understand its foundational elements. Face-to-face learning is the conventional approach where students and instructors interact directly within physical settings like classrooms. In this environment, educators present content, lead discussions, and engage with students actively. In contrast, online learning, which gained prominence during the pandemic, employs digital platforms to facilitate education. This mode enables students to access materials, participate in virtual sessions, and interact with educators and peers from any location, ensuring uninterrupted learning while prioritizing safety.

	Face-to-Face Learning	Online Learning
Instruction	In-person classrooms	Virtual classrooms
Interaction	Direct interaction with peers and instructors	Limited direct interaction with peers and instructors
Flexibility	Limited flexibility in schedule and location	High flexibility in schedule and location
Learning Support	Immediate assistance from instructors	Online resources and support

Table 3. 1: Face-to-Face vs Online Learning Difference

During the pandemic, hybrid teaching emerged as a synchronous blend of in-person and online learning, leveraging platforms like Class.com on Zoom for simultaneous participation (Sultana & Awais, 2022; Goodyear, 2020). This approach, born out of necessity, has proven versatile, catering to local and international students by combining traditional face-to-face benefits with online flexibility (O'Byrne & Pytash, 2015). The research underscores its significance, addressing educational demands, ensuring inclusivity, and preparing students for a digital future by aligning with evolving educational goals and challenges (Abdelrahman & Irby, 2016; Munaro, 2021; McEldoon & Schneider, 2020).

In hybrid learning, students often exhibit varying forms of motivation, primarily categorized as intrinsic and extrinsic. Intrinsic motivation drives individuals to engage in activities for personal satisfaction and enjoyment, promoting high-quality learning and creativity. For instance, intrinsically motivated students find tasks engaging and fulfilling due to their inherent interests. Conversely, extrinsic motivation propels behaviours guided by external rewards or the avoidance of penalties, focusing on external factors rather than intrinsic interest. Recognizing these distinct motivational tendencies among students is vital for designing practical hybrid learning experiences.

Intrinsic Motivation	Extrinsic Motivation
Internal drive and desire to engage in learning	Motivated by external rewards or outcomes
Genuine interest in the subject matter	Driven by grades, recognition, or meeting external expectations
Sense of curiosity and joy of learning	Focused on obtaining certifications or meeting performance targets
Self-motivated and actively seek out opportunities to learn	Engagement may depend on the presence of external incentives

More engaged, persistent, and self-directed	It may have initial motivation, but sustainability may vary.
Motivated by the inherent value and personal meaning of learning	External rewards stimulate engagement initially

Table 3. 2:Intrinsic vs Extrinsic Motivation Difference

Research indicates that learning environments promoting competence, autonomy, and relatedness enhance intrinsic motivation and the assimilation of extrinsic motivations. Notably, students' motivations can evolve; for instance, one might start a semester with intrinsic motivation, only to become more extrinsically motivated as deadlines near. Ultimately, both forms of motivation are vital, and optimal learning environments leverage both by fostering internalization and integration (Ryan & Deci, 2000).

Now that we have identified the various types of motivation in students participating in hybrid learning, let us delve deeper into the surveys and methodologies utilized to assess these distinct motivation levels.

Several validated survey instruments have been developed to measure intrinsic and extrinsic motivation in various contexts, including academic, work, and sports settings, and one such example is the Intrinsic Motivation Inventory(IMI) (Ryan & Deci, Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions, 2000). The IMI is a sophisticated tool introduced by Ryan & R.M. that measures participants' subjective experience related to a specific activity in experimental environments, aligning with their extension of cognitive evaluation theory. The study uses a tool called the Intrinsic Motivation Inventory (IMI) (Ryan & Deci, Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions, 2000) to get a deeper understanding of this. This tool has been widely used in research, with studies by Ostrow & Heffernan and First, Kilinç, & Yüzer (2018) highlighting its reliability. It offers valuable insights into students' motivation, which is crucial when evaluating different teaching methods. It includes the following sub-scales: Interest/Enjoyment, Perceived Competence, Effort/Importance, Pressure/Tension, Perceived Choice, Value/Usefulness, and Relatedness. For More Information, refer to the Appendix C: Intrinsic motivation sub-scales

Key questions this study aims to answer include:

- Do most students lean more towards intrinsic or extrinsic motivation?
- Which learning method do students prefer: hybrid or fully online? And how does this choice relate to their motivation?
- Are there noticeable differences in grades between students in hybrid and online learning?
- How do grades vary between students with different motivations
- In the hybrid learning method, do male students perform differently than female students?
- Is there a connection between the chosen learning method and student motivation?

This study aims to understand how combining online and classroom teaching can help first-year students in their statistics courses. The findings can help teachers improve their classes for all students. The next sections will explain how the study was conducted.

4 METHODOLOGY

4.1 DATA COLLECTION METHODOLOGIES

In the context of the diverse data collection methods utilized in this research, ethical standards and safeguarding measures were consistently upheld to protect the rights and privacy of the participants.

- **Data Management and Anonymity:** All collected student data was initially entrusted to a research assistant removed from teaching or academic responsibilities. This separation ensured the impartial matching and deidentification of the data, preserving the anonymity of student participants and mitigating potential biases.
- **Storage and Access:** After the meticulous process of cleaning and matching, the data was stored in a cloud-based repository. This repository was designed with stringent access controls, ensuring data could only be accessed after its deidentification.
- **Informed Consent:** Before the commencement of the study, all participating students were made aware of the type of data that would be collected, its intended purpose, and the rigorous measures in place for its handling. This transparency ensured that students clearly understood the research process and how their information would be used.
- **Bias Minimization:** By delegating sensitive student data management to a research assistant without direct teaching or grading responsibilities, the research was safeguarded against potential instructor biases, ensuring that data integrity and student trust were maintained.

By adhering to these rigorous ethical guidelines, the research aimed to uphold the highest standards of integrity, trustworthiness, and respect for all participants involved.

With ethical considerations, the study proceeded with its systematic data collection approach. The initial step involved inviting student volunteers, resulting in a group of 126 participants with an average age of 21.5(SD=6.7). These participants were then allocated to specific learning modalities: 64 were assigned to the hybrid mode with an average age of 22 (SD = 8.8). At the same time, 62 were designated for the online mode with an average age of 20.9 (SD = 5), achieved through a randomized stratification method.

Primary data sources encompassed the Student Information System, the Learning Management System (LMS), and the Intrinsic Motivation Inventory (IMI) (Ryan & Deci, Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions, 2000). These platforms offered insights into student engagement and satisfaction levels. Additionally, metrics such as focus time were extracted from class.com.

In essence, refer to the flowchart in *Fig.1* that provides a concise roadmap of our data collection journey, highlighting key stages and tools employed.

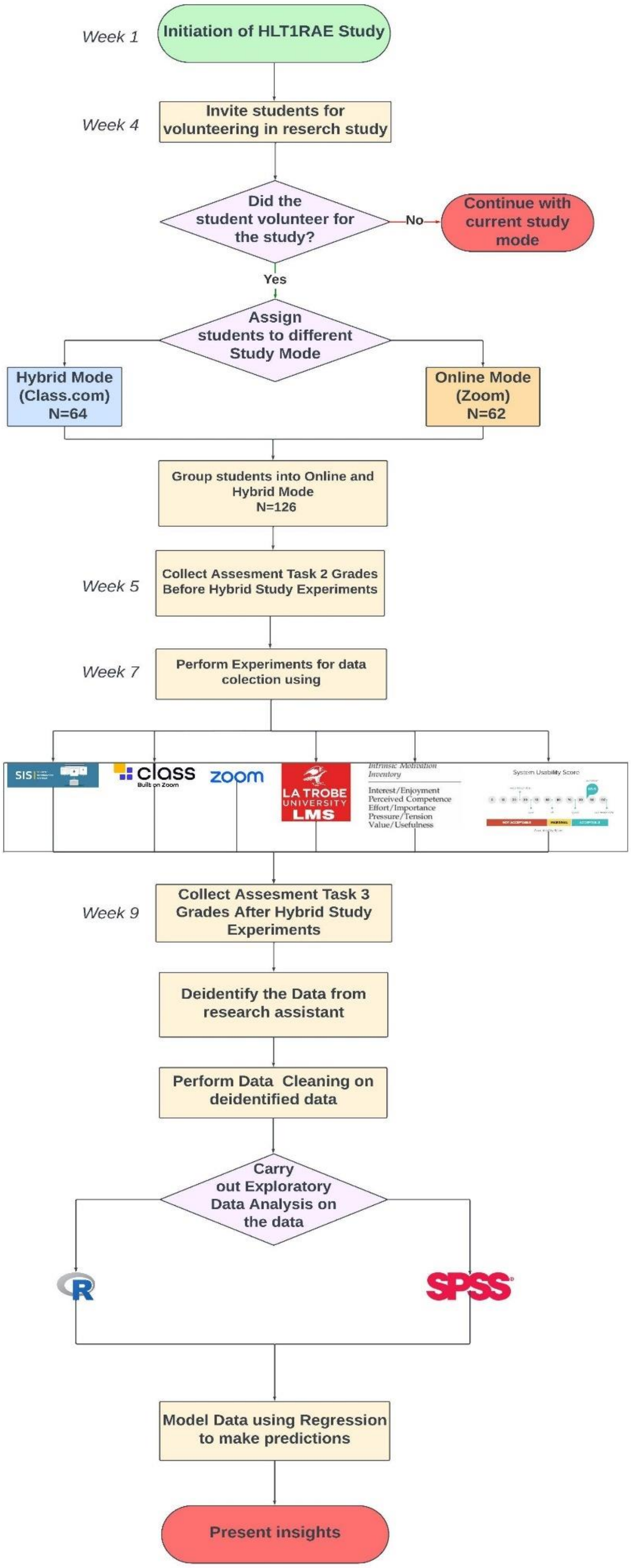
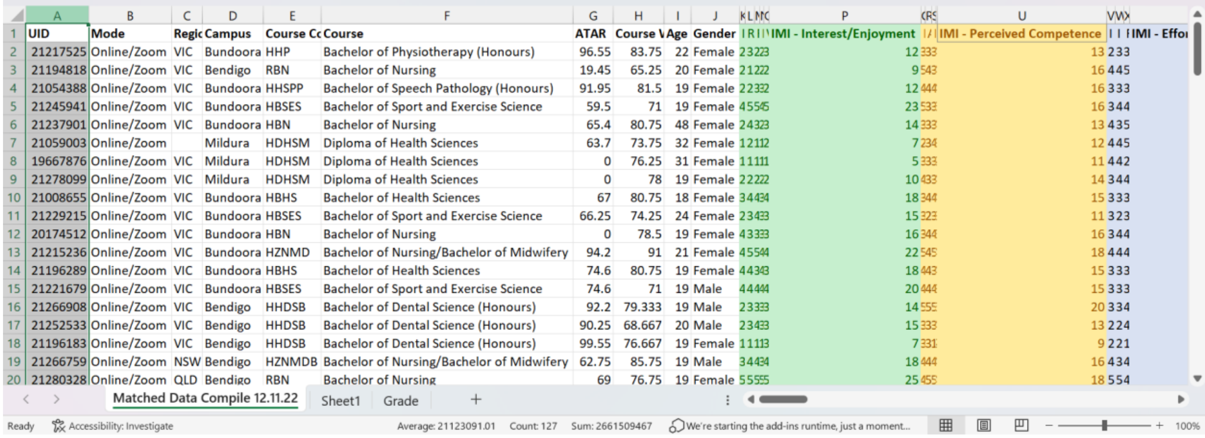


Figure 4.1. 1:Flowchart - Data Collection Process for Hybrid Teaching on Students with Intrinsic and Extrinsic Motivation

4.1.1 Limitations of Dataset:



	UID	Mode	Regic	Campus	Course Cc	Course	ATAR	Course \	Age	Gender	IRII\	IMI - Interest/Enjoyment	I/I	IMI - Perceived Competence	I I I	IMI - Effor
2	21217525	Online/Zoom	VIC	Bundoora	HHP	Bachelor of Physiotherapy (Honours)	96.55	83.75	22	Female	23223	12	333	13	233	
3	21194818	Online/Zoom	VIC	Bendigo	RBN	Bachelor of Nursing	19.45	65.25	20	Female	21222	9	543	16	445	
4	21054388	Online/Zoom	VIC	Bundoora	HHSPP	Bachelor of Speech Pathology (Honours)	91.95	81.5	19	Female	22332	12	444	16	333	
5	21245941	Online/Zoom	VIC	Bundoora	HBSES	Bachelor of Sport and Exercise Science	59.5	71	19	Female	45545	23	533	16	344	
6	21237901	Online/Zoom	VIC	Bundoora	HBN	Bachelor of Nursing	65.4	80.75	48	Female	24323	14	333	13	435	
7	21059003	Online/Zoom		Mildura	HDHSM	Diploma of Health Sciences	63.7	73.75	32	Female	12112	7	234	12	445	
8	19667876	Online/Zoom	VIC	Mildura	HDHSM	Diploma of Health Sciences	0	76.25	31	Female	11111	5	333	11	442	
9	21278099	Online/Zoom	VIC	Mildura	HDHSM	Diploma of Health Sciences	0	78	19	Female	22222	10	433	14	344	
10	21008655	Online/Zoom	VIC	Bundoora	HBHS	Bachelor of Health Sciences	67	80.75	18	Female	34434	18	344	15	333	
11	21229215	Online/Zoom	VIC	Bundoora	HBSES	Bachelor of Sport and Exercise Science	66.25	74.25	24	Female	23433	15	323	11	323	
12	20174512	Online/Zoom	VIC	Bundoora	HBN	Bachelor of Nursing	0	78.5	19	Female	43333	16	344	16	344	
13	21215236	Online/Zoom	VIC	Bundoora	HZNMD	Bachelor of Nursing/Bachelor of Midwifery	94.2	91	21	Female	45544	22	545	18	444	
14	21196289	Online/Zoom	VIC	Bundoora	HBHS	Bachelor of Health Sciences	74.6	80.75	19	Female	44343	18	443	15	333	
15	21221679	Online/Zoom	VIC	Bundoora	HBSES	Bachelor of Sport and Exercise Science	74.6	71	19	Male	44444	20	444	15	333	
16	21266908	Online/Zoom	VIC	Bendigo	HHDSB	Bachelor of Dental Science (Honours)	92.2	79.333	19	Male	23333	14	555	20	334	
17	21252533	Online/Zoom	VIC	Bendigo	HHDSB	Bachelor of Dental Science (Honours)	90.25	68.667	20	Male	23433	15	333	13	224	
18	21196183	Online/Zoom	VIC	Bendigo	HHDSB	Bachelor of Dental Science (Honours)	99.55	76.667	19	Female	11113	7	331	9	221	
19	21266759	Online/Zoom	NSW	Bendigo	HZNMDB	Bachelor of Nursing/Bachelor of Midwifery	62.75	85.75	19	Male	34434	18	444	16	434	
20	21280328	Online/Zoom	QLD	Bendigo	RBN	Bachelor of Nursing	69	76.75	19	Female	55555	25	455	18	554	

Matched Data Compile 12.11.22 | Sheet1 | Grade

Ready | Accessibility: Investigate | Average: 21123091.01 | Count: 127 | Sum: 2661509467 | We're starting the add-ins runtime, just a moment... | 100%

Figure 4.1.1 1:Hybrid teaching dataset

The participant recruitment process yielded a modest number of student volunteers, resulting in a dataset of limited size. In the realm of statistical and data modelling, such constraints can introduce specific challenges:

- **Model Robustness:** A smaller dataset might not capture the total variability of the population. Consequently, models developed from this data might not be as robust, potentially leading to overfitting where the model performs well on the training data but may not generalize well to new, unseen data.
- **Detection of Subtle Patterns:** Limited data can hinder the ability to discern nuanced patterns or relationships. This constraint can affect the depth of insights, potentially overlooking subtle but important trends or correlations that might be more evident with a larger dataset.

It's essential to approach analysis with these limitations, ensuring that recognising these challenges tempers conclusions drawn.

4.2 DATA ANALYSIS METHODOLOGIES

The present study's dataset comprises data from 126 participants, encompassing 33 variables. Among these variables, 21 are primary and provide detailed information about student attributes. The dataset includes essential information, such as "UID," serving as a unique identifier for each student, and the "Mode" variable, indicating the teaching method used, either Hybrid or Online. The variable "Region origin" classifies students into four distinct regions: Victoria, New South Wales, Queensland, and Western Australia, providing insights into potential cultural differences. Additionally, the "Campus" variable specifies the location where the subjects are taught, highlighting any campus-specific distinctions. The variables "Course Code" and "Course" act as identifiers for different courses, enabling comparisons between them. Notably, regardless of the course, all students are studying Health Science. Academic performance in Australia is represented by the "ATAR"(Australian Tertiary Admission

Rank) (Australian Tertiary Admission Rank, 2023) variable, while the "Course/Subject Weighted Average" offers information about the students' average performance in the statistics subject*(For further elaboration, please refer Appendix A and Appendix B)*.

Furthermore, "Age" and "Gender" provide valuable insights into age and gender-related learning preferences. Contained within the dataset are "IMI Variables," metrics originating from the Intrinsic Motivation Inventory (Ryan & Deci, Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions, 2000). These metrics delineate intricate details regarding student motivation levels, specifically within the hybrid teaching environment *(For further elaboration, please refer to Appendix C)*. Moreover, the "SUS (System Usability Scale)" captures perceptions of usability based on a questionnaire, with a method in place to derive overall SUS scores from individual responses*(For further elaboration, please refer to Appendix D)*. Another significant variable is "Focus time," explicitly measuring the duration students dedicate to focused academic activities when using the class.com software. Lastly, additional variables capture ratings and feedback on the hybrid teaching model. This study focuses on the dependent variable "AT 3: Critical appraisal essay Week 9", representing grades obtained after introducing the hybrid teaching mode. The dataset also includes "AT2 article summary Week 5," reflecting grades acquired before this teaching transition. The remaining variables act as predictors or independent variables in the analysis.

The data analysis process in this research was comprehensive and multifaceted. Initially, data exploration was conducted to gain a preliminary understanding of the dataset's structure, variables, and potential patterns. This exploration phase provided a bird's-eye view of the data, highlighting areas that required further attention. Subsequently, data was cleaned to address inconsistencies, outliers, or missing values, ensuring the dataset's integrity and reliability. With a cleaned dataset, descriptive statistics were then employed to offer insights into its central tendencies, dispersion, and distribution shape, serving as the foundation for further analyses. The data underwent additional pre-processing tasks, such as transforming variables and encoding categorical data, to refine and prepare it for deeper analytical procedures. Various statistical tests followed, ascertaining relationships between variables, testing hypotheses, and validating assumptions. These tests ensured that the findings were grounded in rigorous statistical evidence. Concluding the analysis, advanced data modelling techniques, including linear regression and regression trees, were employed to uncover deeper insights and patterns within the data. These models aimed to predict outcomes, understand variable relationships and offer a more profound understanding of the underlying data structures.

The dataset includes 126 participants and 33 variables, focusing on student attributes, teaching methods, regional origin, academic performance, age, gender, motivation levels, usability perceptions, focused academic activities, and feedback on the hybrid teaching model.

5 RESULTS

5.1 DATA EXPLORATION

After acquainting ourselves with the dataset's variables and the analytical methods used, we proceed to the first stage of our study: Exploratory data analysis. This phase is crucial as it allows us to understand and outline the dataset's main attributes before conducting a more detailed analysis.

Data exploration presents a clear and concise snapshot of the data, allowing one to spot patterns and unusual values and grasp the dataset's main features. This knowledge sets the stage for more complex analyses down the road.

The primary objective is to examine the distinctions between the Online and Hybrid teaching modes. An initial step involves analysing the descriptive statistics for the "Mode" variable, facilitating a structured understanding of the disparities between these modalities.

	Hybrid/Class.com (N=64)	**Online/Zoom (N=62)**	**Overall (N=126)**	**p-value**
Age Mean(± SD)	21 (± 7.6)	22 (± 5.7)	22 (± 6.7)	0.357
ATAR Mean(± SD) Missing N(%)	75 (± 18) 6 (9.4%)	72 (± 17) 11 (17.7%)	74 (± 17) 17 (13.5%)	0.201
Course Weighted Average Mean(± SD)	72 (± 15)	75 (± 8.6)	74 (± 12)	0.714
AT2 Mean(± SD) Missing N(%)	16 (± 1.8) 5 (7.8%)	16 (± 2.7) 1 (1.6%)	16 (± 2.3) 6 (4.8%)	0.715
AT3 Mean(± SD) Missing N(%)	75 (± 15) 2 (3.1%)	75 (± 12) 4 (6.5%)	75 (± 13) 6 (4.8%)	0.120
IM_Percentage Mean(± SD)	67 (± 11)	66 (± 14)	66 (± 12)	0.304
EM_Percentage Mean(± SD)	63 (± 9.1)	59 (± 13)	61 (± 11)	0.041

Table 5.1. 1:Descriptive statistics for the mode of study

The table offers insights into the differences and similarities between two educational delivery methods: "Hybrid/Class.com" and "Online/Zoom." Regarding age, both modes have a nearly identical average, hovering around 22 years. This suggests that the age distribution of participants in both groups is similar. When we focus on the ATAR scores, the "Hybrid/Class.com" group has a slightly higher average score of 75 than the "Online/Zoom" group's average of 72. However, this difference isn't statistically significant, as evidenced by the p-value of 0.201. In the course weighted average context, the "Online/Zoom" mode has a marginally higher mean score of 75, compared to 72 for the "Hybrid/Class.com" mode. Yet, this difference isn't statistically significant either, with a p-value of 0.714. However, both modes display similar performance levels for the "AT2" and "AT3," with averages close to 16 and 75, respectively. This suggests that the mode of delivery doesn't significantly impact student performance in these assessments. Lastly, in terms of motivation percentages (both intrinsic and extrinsic), both modes show comparable results. The "Hybrid/Class.com" mode averages 67 and 63 for intrinsic and extrinsic motivations, respectively, while the "Online/Zoom" mode averages 66 and 59. These differences aren't statistically significant, as indicated by their respective p-values.

In conclusion, the data presented in the table offers a preliminary understanding of the performance and characteristics of students across two educational delivery methods. Further detailed analysis would be beneficial to delve deeper into these findings.

After understanding the statistics summary of Hybrid and Online Mode, lets drill in more and see the descriptive statistics of Mode and Motivation type, Motivation Type and Gender, Mode and Gender.

	Hybrid/Class.com (N=64)		**Online/Zoom (N=62)**		**Overall (N=126)**		**p-value**
	Extrinsic (N=21)	Intrinsic (N=43)	Extrinsic (N=19)	Intrinsic (N=43)	Extrinsic (N=40)	Intrinsic (N=86)	
Age Mean(± SD)	20 (± 3.5)	22 (± 9.0)	24 (± 8.5)	21 (± 3.6)	22 (± 6.6)	21 (± 6.8)	0.052
ATAR Mean(± SD)	71 (± 19)	78 (± 17)	72 (± 15)	72 (± 18)	71 (± 17)	75 (± 17)	0.342
Missing N(%)	2 (9.5%)	4 (9.3%)	3 (15.8%)	8 (18.6%)	5 (12.5%)	12 (14.0%)	
Course Weighted Average Mean(± SD)	73 (± 13)	72 (± 16)	74 (± 11)	76 (± 7.0)	74 (± 12)	74 (± 13)	0.422
AT2 Mean(± SD)	16 (± 1.8)	16 (± 1.9)	16 (± 2.8)	16 (± 2.6)	16 (± 2.3)	16 (± 2.3)	0.625
Missing N(%)	1 (4.8%)	4 (9.3%)	0 (0%)	1 (2.3%)	1 (2.5%)	5 (5.8%)	
AT3 Mean(± SD)	70 (± 19)	77 (± 12)	77 (± 14)	74 (± 11)	74 (± 17)	76 (± 11)	0.071
Missing N(%)	1 (4.8%)	1 (2.3%)	2 (10.5%)	2 (4.7%)	3 (7.5%)	3 (3.5%)	
IM_Percentage Mean(± SD)	61 (± 7.4)	70 (± 11)	59 (± 16)	68 (± 12)	60 (± 12)	69 (± 11)	0.985
EM_Percentage Mean(± SD)	66 (± 6.2)	61 (± 10)	61 (± 17)	58 (± 11)	64 (± 12)	60 (± 10)	0.707

Table 5.1. 2:Data exploration for the mode of study and motivation type variables

The provided table furnishes descriptive statistics for the "Hybrid/Class.com" and "Online/Zoom" teaching modes, further categorized by Extrinsic and Intrinsic Motivation categories. This detailed breakdown enhances our comprehension of the relationship between teaching approaches and student motivation. Concerning age, students displaying Extrinsic motivation in the "Hybrid/Class.com" mode exhibit a mean age of 20. In contrast, those driven by Intrinsic motivation have an average age of 22. In the "Online/Zoom" mode, the mean age is 24 for Extrinsic motivation and 21 for Intrinsic motivation. This discrepancy implies differing age patterns associated with distinct motivational orientations across the two teaching modes.

Regarding ATAR scores, students in the "Hybrid/Class.com" mode with Extrinsic motivation attain a mean score of 71, while their counterparts with Intrinsic motivation achieve a slightly higher mean score of 78. In contrast, the "Online/Zoom" mode demonstrates a consistent mean ATAR score of 72 for both motivation types. Course Weighted Averages exhibit relative uniformity across modes and motivation types, with scores predominantly hovering around the mid-70s. Specific assignments such as AT2 and AT3 show minimal variation between the modes and motivation types, with scores generally averaging around 16 and the mid-70s, respectively. Concerning motivation percentages, the "Hybrid/Class.com" mode records a higher mean for Intrinsic Motivation. In contrast, the "Online/Zoom" mode slightly leans towards Extrinsic Motivation. This differentiation provides insight into how varying teaching methods may influence or align with students' motivational tendencies.

	Hybrid/Class.com (N=64)		**Online/Zoom (N=62)**		**Overall (N=126)**		**p-value**
	Female (N=49)	Male (N=15)	Female (N=47)	Male (N=15)	Female (N=96)	Male (N=30)	
Age Mean(± SD)	22 (± 8.6)	19 (± 1.5)	22 (± 6.0)	22 (± 4.8)	22 (± 7.4)	20 (± 3.7)	0.319
ATAR Mean(± SD)	76 (± 17)	74 (± 20)	72 (± 18)	72 (± 14)	74 (± 17)	73 (± 17)	0.780
Missing N(%)	4 (8.2%)	2 (13.3%)	6 (12.8%)	5 (33.3%)	10 (10.4%)	7 (23.3%)	
Course Weighted Average Mean(± SD)	73 (± 15)	71 (± 14)	76 (± 8.2)	74 (± 9.7)	74 (± 12)	73 (± 12)	0.986
AT2 Mean(± SD)	16 (± 1.7)	16 (± 2.1)	16 (± 2.2)	15 (± 3.7)	16 (± 2.0)	15 (± 3.0)	0.695
Missing N(%)	4 (8.2%)	1 (6.7%)	1 (2.1%)	0 (0%)	5 (5.2%)	1 (3.3%)	
AT3 Mean(± SD)	75 (± 13)	73 (± 19)	77 (± 12)	72 (± 11)	76 (± 13)	72 (± 15)	0.641
Missing N(%)	2 (4.1%)	0 (0%)	4 (8.5%)	0 (0%)	6 (6.3%)	0 (0%)	
IM_Percentage Mean(± SD)	67 (± 11)	67 (± 10)	65 (± 15)	69 (± 9.7)	66 (± 13)	68 (± 9.9)	0.409
EM_Percentage Mean(± SD)	62 (± 9.5)	65 (± 8.0)	59 (± 14)	62 (± 8.2)	60 (± 12)	63 (± 8.1)	0.910

Table 5.1. 3:Data exploration for Mode and Gender

The table above offers a detailed breakdown of descriptive statistics categorized by teaching modes, "Hybrid/Class.com" and "Online/Zoom," further separated by gender. Looking at age, we observe that in the "Hybrid/Class.com" mode, the mean age for females is 22.1 years, while for males, it's 19.2 years. In the "Online/Zoom" mode, females have a mean age of 21.7 years, and males have a mean age of 21.7 years, indicating some potential gender-based age differences within these modes. Moving on to ATAR scores, both genders in the "Hybrid/Class.com" mode tend to have slightly higher means than their counterparts in the "Online/Zoom" mode. Similarly, when considering Course Weighted Averages, the "Hybrid/Class.com" mode shows higher means for female and male students than the "Online/Zoom" mode. Analyzing System Usability (SUS) scores, we find that females in the "Online/Zoom" mode tend to have higher means, suggesting a more user-friendly experience for this group. However, for variables like "AT2" and "AT3," there are no significant gender disparities across both teaching modes, with scores showing similar results. Regarding motivation percentages, both modes tend to have slightly higher mean percentages for Intrinsic and Extrinsic Motivation among female students, although these differences are not substantial. This information contributes to understanding how teaching modes and gender may intersect and influence various academic aspects.

5.1.1 Count analysis for Motivation Type and Likeness for Hybrid Mode

After grasping the concept of central tendencies, let's delve into a categorical count analysis to determine whether students tend to be more intrinsically or extrinsically motivated. Additionally, we'll investigate the prevalence of students who favour the Hybrid Mode. Furthermore, we'll examine the subset of students who are intrinsically motivated and inclined towards the Hybrid Mode. This analysis will provide a comprehensive perspective on the motivational and mode preferences of the students.

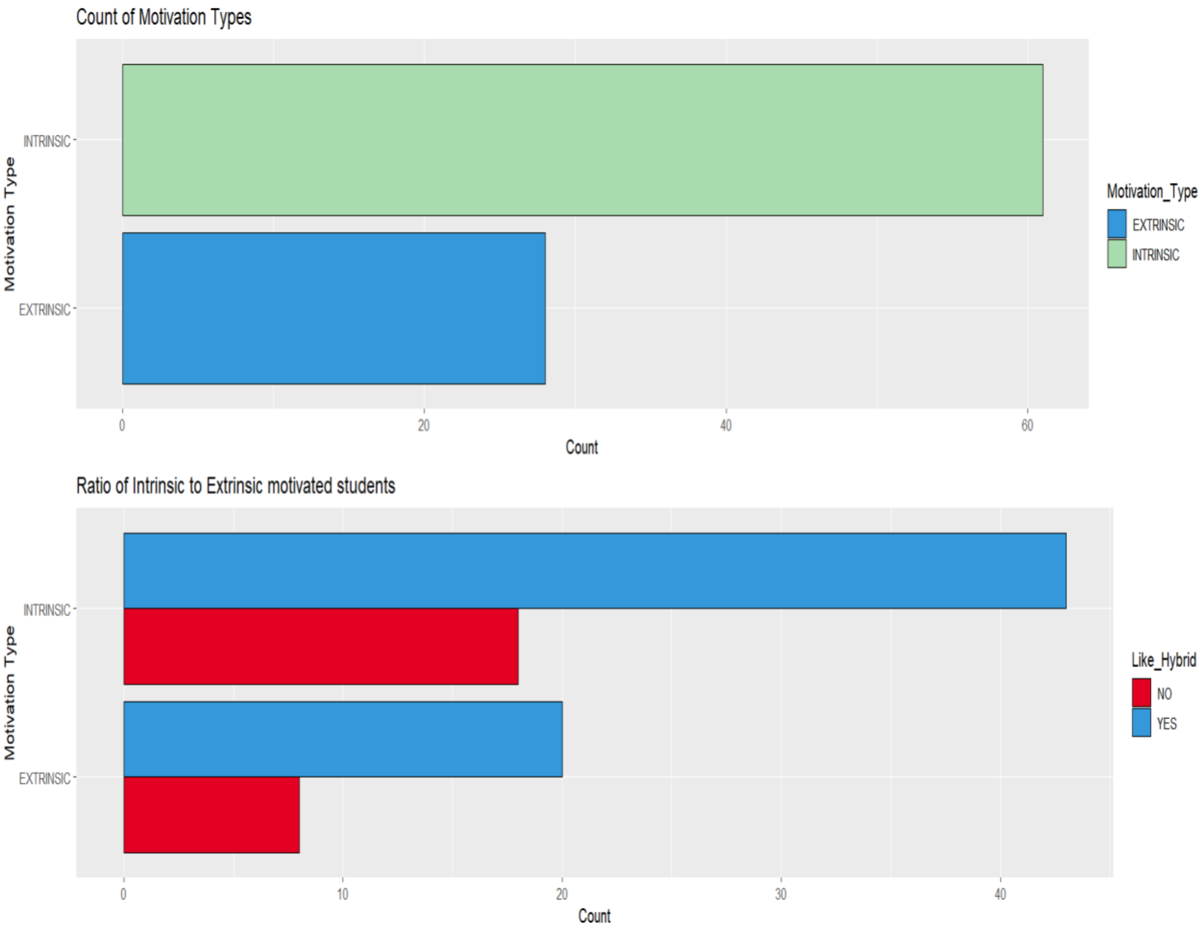


Figure 5.1.1. 1:Count Plot for Motivation Type

Based on the provided count plot above, it's evident that a significant majority of students, approximately 68.54%, exhibit intrinsic motivation.

In the presented bar plot, an evident trend towards intrinsic motivation is observed for both categories, irrespective of their inclination towards hybrid learning. The ratios, 2.25 for the "NO" group and 2.15 for the "YES" group are closely aligned, indicating that the type of motivation might not solely govern the preference for hybrid learning. While intrinsic motivations, driven by personal interests and satisfaction, appear dominant in both groups, the exact impact of these motivations on hybrid learning preference remains questionable and warrants further investigation.

5.1.2 Exploring Categorical vs Numerical distribution

Up to this point, we have conducted observations and explorations involving categorical variables exclusively. Now, we will focus on exploring the distribution between categorical and numerical variables. Specifically, we will investigate whether there are variations in AT3 grades across different Genders, modes of learning, Motivation types, and Likeness for Hybrid. This analysis is essential as it aids our understanding of academic performance.

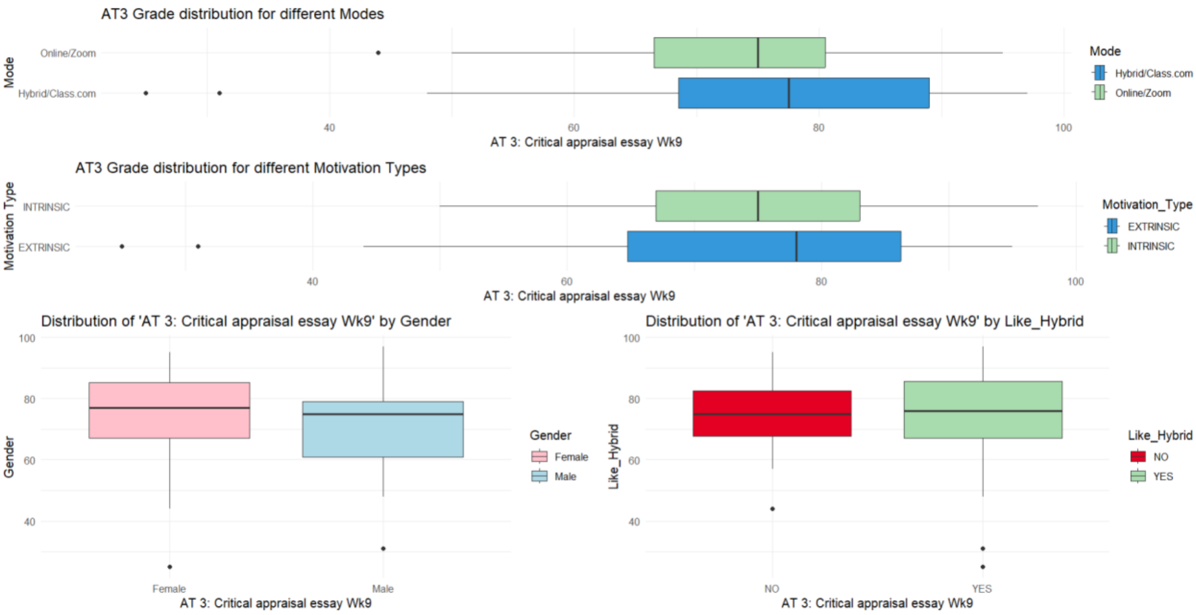


Figure 5.1.2. 1:AT3 distribution for Different Study Modes

Based on the boxplot depicted above, it is evident that the median grade for the Hybrid mode surpasses that of the Online mode. This observation suggests that students enrolled in the Hybrid mode exhibit better performance, as reflected in their higher AT3 grades than in the Online mode.

Although the differences may not be substantial initially, a closer look at the boxplots suggests that intrinsically motivated students tend to have lower AT3 grades than extrinsically motivated students.

Now, let's examine whether there are variations in grades across different genders.

In an examination of the box plots representing scores for 'AT3', it is evident that there are notable differences based on gender and preference for a hybrid mode of study. On average, female participants scored higher than their male counterparts, with a median score close to 90 for females and approximately 70 for males. Moreover, the score distribution for males showed more significant variability. When analysing preferences for the hybrid mode, those not favouring it generally achieved higher scores, with a median near 80. In contrast, participants who preferred the hybrid mode had a median score closer to 70 and displayed a broader score range, suggesting a diverse performance within this group.

5.1.3 Exploring the Distribution of Variables

After analysing the count plots, let's now focus on understanding the distribution of variables using the Shapiro-Wilk normality test, which offers further insights into the dataset.

Variable	p-value	Distribution
Age	1.563e-16	Not Normally Distributed
AT2	2.768e-11	Not Normally Distributed
AT3	0.0007	Not Normally Distributed
ATAR	0.0007	Not Normally Distributed
Course Weighted Average	1.368e-07	Not Normally Distributed
IMI - Interest/Enjoyment	0.045	Not Normally Distributed
IMI - Perceived Competence	0.012	Not Normally Distributed
IMI - Effort/Importance	0.014	Not Normally Distributed
IMI - Pressure/Tension	0.009	Not Normally Distributed
IMI - Perceived Choice	0.172	Normally Distributed
IMI - Value/Usefulness	0.05	Normally Distributed
IMI – Relatedness	0.085	Normally Distributed
IM_Percentage	0.410	Normally Distributed
EM_Percentage	0.03	Not Normally Distributed
TOTAL	1.203e-07	Not Normally Distributed

Table 5.1.3. 1: Understanding the distribution of several variables using the Shapiro-wilk test

The "Age" variable significantly differs from a normal distribution, as indicated by its low p-value of 1.563e-16. Similarly, "AT2" and "Course Weighted Average" have p-values of 2.768e-11 and 1.368e-07, respectively, suggesting non-normal distributions. "AT3" and "ATAR", with p-values of 0.0007, deviate slightly from normality. Among the intrinsic motivation indices, "IMI - Interest/Enjoyment", "IMI - Perceived Competence", "IMI - Effort/Importance", and "IMI - Pressure/Tension" all show signs of non-normal distribution with p-values less than 0.05. However, "IMI - Perceived Choice", "IMI - Relatedness", and "IM_Percentage" have p-values greater than 0.05, indicating they might be closer to a normal distribution. "EM_Percentage" with a p-value of 0.03 and "TOTAL" with a p-value of 1.203e-07 also deviate from a normal distribution.

In simpler terms, many of the variables in the study, such as "Age", "AT2", "AT3", and "ATAR", don't follow a typical bell-shaped curve. Only a few, like "IMI - Perceived Choice" and "IMI - Relatedness", might exhibit a distinct distribution pattern.

5.1.4 Exploring extreme values using Box-plot analysis

Having completed the analysis of central tendencies for variables such as Mode, Motivation Type, and Gender and the distribution of variables through histograms, we are well-positioned to move on to a more intricate level of scrutiny. Next, we'll focus on outlier analysis to identify any significant deviations that may be anomalies within our dataset.

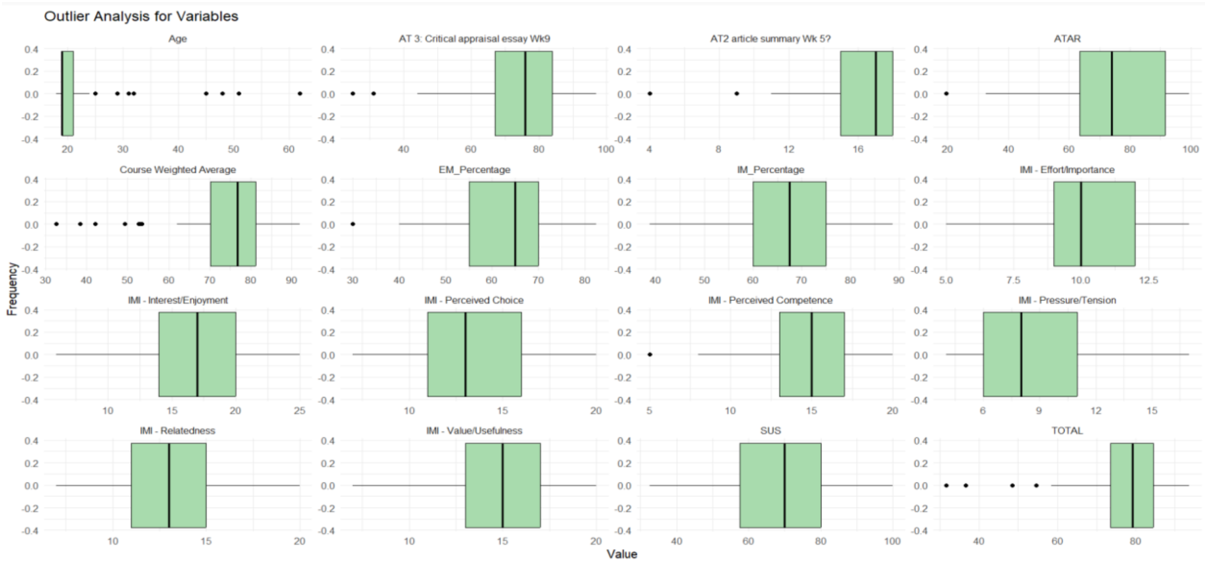


Figure 5.1.4. 1:Extreme value analysis for Hybrid and Online

Int intriguing patterns and insights emerged as we delved into the dataset, giving us a closer look at how different variables are distributed and what stands out as unusual. Starting with ages, most students fall between 18 and 22, which makes up the majority. Interestingly, there are also students older than 25, showing a mix of age groups in education. What's even more eye-catching is a handful of students aged 50 and above still pursuing their studies – quite a diverse age range. Shifting gears to grades, after the Hybrid Mode intervention, AT3 grades seem to gather around 63 to 84, and only a couple are on the lower end, below 40. This hints at improvement due to the intervention. AT2 grades seem tighter, mainly between 14 and 21, with only a few grades below 10. Like AT3, ATAR scores huddle around 62 to 86, with one student's score at 20 raising an eyebrow. For overall performance, the course weighted average (CWA) clusters around 70 to 81, but there are a few cases where CWA goes below 55. Extrinsically motivated students mostly score between 55 and 70, though one outlier at 30 might have a unique motivation story. Lastly, when it comes to total marks, they spread between 67 and 87 for the majority. However, a few students have scores below 55, signalling possible challenges they faced.

These insights together paint a vivid picture of the dataset, giving us a glimpse into student demographics, performance trends, and areas worth investigating further.

Just as we observed overall outliers, let’s now focus on drilling in outliers analysis concerning variables like Mode and Motivation Type.

Beginning with the Mode variable, we'll first investigate the presence of outliers for both Hybrid and Online modes. This step will provide valuable insights into exceptional data points beyond the typical patterns, complementing the central tendency analysis we've already conducted.

Upon conducting a box plot analysis for variables associated with the Hybrid mode, noteworthy observations have emerged.

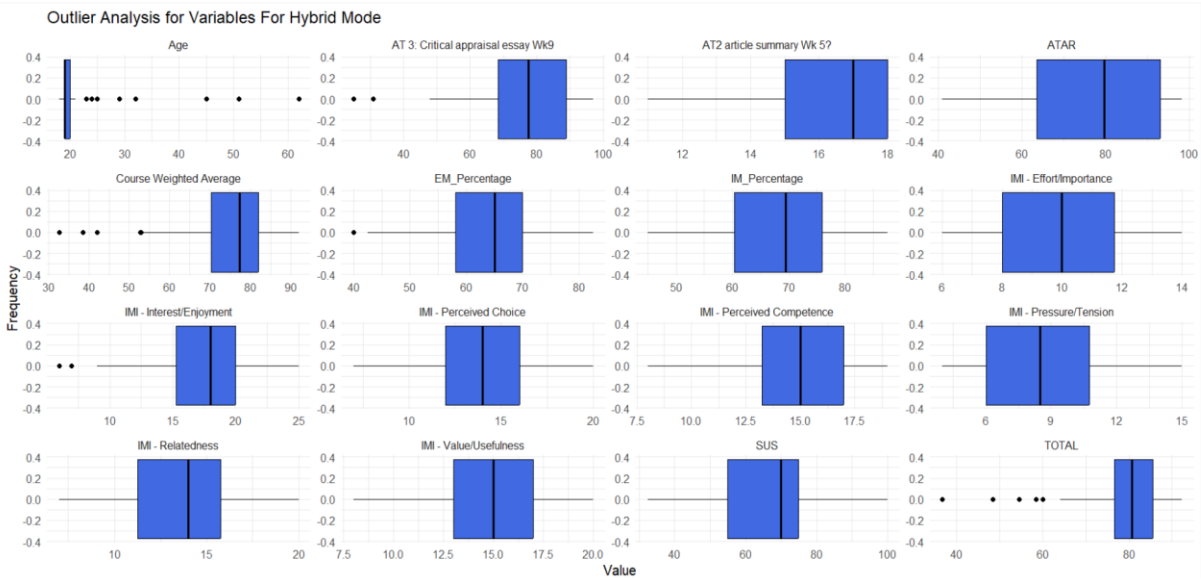


Figure 5.1.4. 2:Extreme value analysis for variables in Hybrid Mode

Notably, the "Age" column displays eight outliers extending beyond the lower quartile, with the box plot's interquartile range spanning from 20 to 23. Similarly, the "Course Weighted Average" exhibits three outliers within the scope of 30 to 45. Additionally, the variable "Interest/Enjoyment" indicates two outliers below a value 5. Moreover, with the "Total Grade," five outliers are observed falling below the threshold of 60. These insights collectively contribute to a comprehensive understanding of the data distribution and potential anomalies within the Hybrid mode dataset.

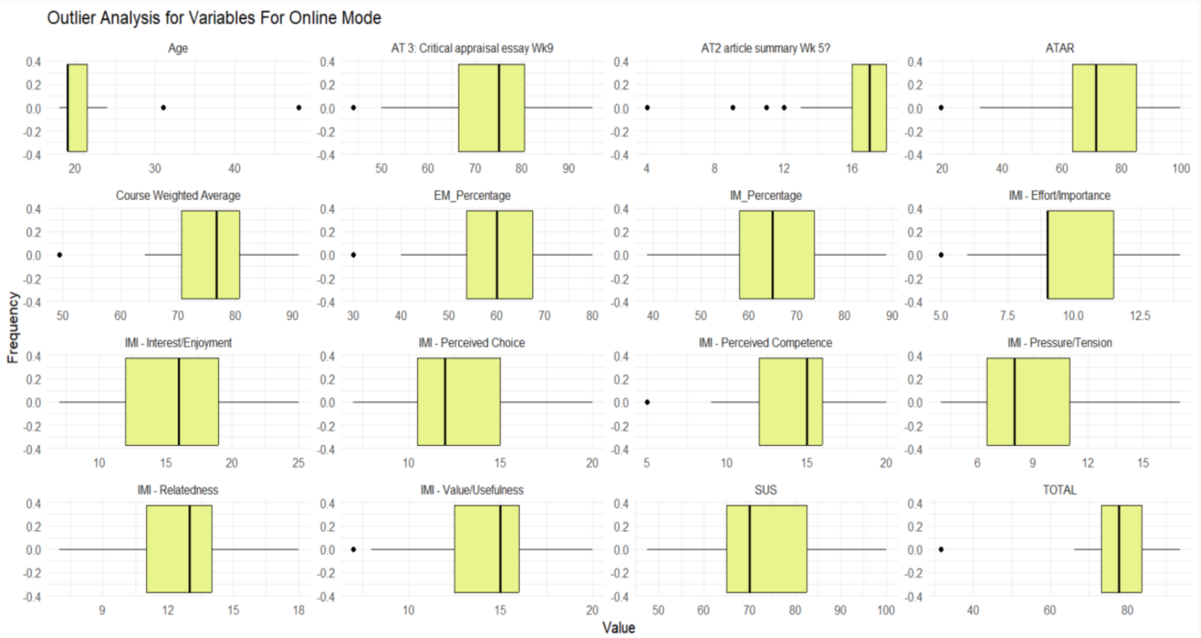


Figure 5.1.4. 3:Extreme value analysis for variables in Online Mode

The former exhibits fewer outliers when contrasting the Online mode with the Hybrid mode. Specifically, the "Age" variable for the Online mode presents two outliers exceeding the value 30. The "Course Weighted Average" reveals a singular outlier, approximately at 50. The "Total Grade" variable also indicates one outlier positioned below 40. These observations suggest a relatively more consistent data distribution for the Online mode compared to the Hybrid mode, underscoring the nuances between the two teaching modalities.

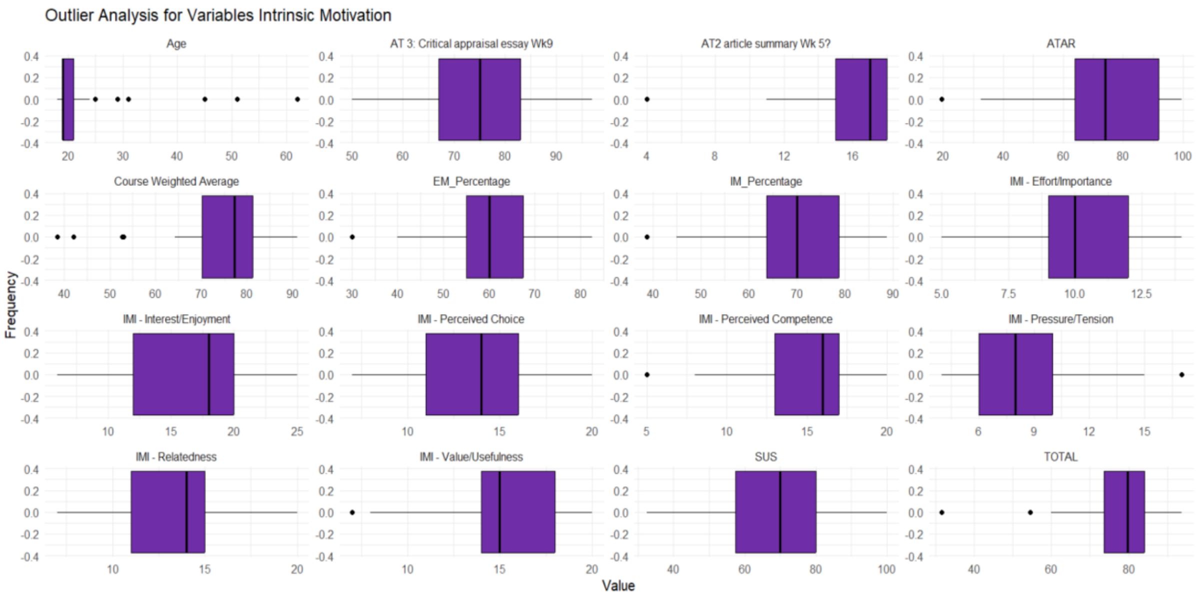


Figure 5.1.4. 4:Extreme value analysis for variables for Intrinsic Motivation

From the above figure, the boxplot reveals several noteworthy observations. First, the variable “Age” shows six outliers above 25. Three of these outliers fall within the age range of 25 to 34, while the remaining three are within the 45 to 65 age bracket. This suggests that individuals in these age categories may have distinct levels of intrinsic motivation compared to the broader study population.

Second, the variable “ATAR” has a single outlier at a score of 20, implying that at least one individual whose ATAR score significantly deviates from the central tendency of the data. This could potentially affect the reliability of ATAR as a predictor for intrinsic motivation within this dataset.

Third, “Course Weighted Average” displays four outliers, all below the score of 55. This may indicate that these individuals' academic performance is not aligned with the general trend of the data and could have unique factors affecting their intrinsic motivation towards coursework.

Lastly, two variables related to motivation, “Intrinsic Motivation Percentage (IM Percentage)” and “Total,” each have outliers as well. IM Percentage has one outlier at 40, which could signify an individual with a shallow level of intrinsic motivation. For the “Total” variable, two outliers fall below the score of 60, indicating that these individuals exhibit significantly different overall scores when all variables are considered.

Collectively, these outliers serve as focal points for further investigation, as they may harbour unique insights into the relationship between these variables and intrinsic motivation.

5.2 DATA CLEANING

Upon completing the descriptive statistics, which provided insights into Mode, Motivation Type, and Gender, the next crucial phase in exploratory data analysis is Data Cleaning.

Data Cleaning meticulously scrutinises the dataset to identify and rectify errors, discrepancies, and inaccuracies. This phase is pivotal as unrefined data often contains anomalies that can skew the analysis, potentially leading to erroneous conclusions. Refining the data enhances its reliability and accuracy, ensuring it is primed for comprehensive analysis. This refinement encompasses eliminating aberrant values, addressing missing data, standardizing formats, and rectifying any identified mistakes. Proper data cleaning paves the way for deriving trustworthy and significant insights, ensuring the dataset is optimized for subsequent in-depth analyses.

Outlined below are the specific data-cleaning procedures that will be undertaken for this research:

5.2.1 Dropping irrelevant columns from the dataset

To refine and concentrate our dataset, columns that do not directly contribute to the core of our analysis were discarded from the dataset. The columns that have been omitted include:

- **UID:** This unique identifier does not provide substantial insight into our analysis objectives.
- **Course Code and Course:** Given that all participants are enrolled in Health Science, these columns do not offer additional meaningful information.
- **Course Weighted Average:** We dropped this column because we found that during the preliminary analysis of regression, this variable was found to be statistically insignificant.
- **Region Origin:** The column denotes the region from where the participant belongs; hence, this doesn't provide any significant relevance to the analysis like the UID column
- **IMI Questions:** We have decided to forego individual IMI questions since we are utilizing IMI subscales to assess intrinsic motivation (as elaborated in Intrinsic Motivation Questions).
- **SUS Questions:** Likewise, we have excluded individual SUS questions as the overall SUS score suffices for our evaluation of usability perceptions.
- **Focus Time:** It's worth noting that the "Focus Time" column contains many missing values. This occurrence can be attributed to the fact that focus time measurements apply exclusively to students engaged in the Hybrid teaching mode, rendering this data irrelevant for students utilizing the online mode. Given that this column does not offer meaningful insights for our comprehensive analysis, we have removed it from our dataset.

By eliminating these extraneous columns, our dataset focuses solely on variables directly pertinent to our research. This strategic selection ensures that our analysis remains tightly aligned with the fundamental objectives of our study. It's important to note that this decision is a crucial aspect of our initial report assessment for the master's level study.

5.2.2 Dealing with Missing values

After removing unnecessary columns from our dataset, our attention now shifts to ensuring the dataset is accurate and reliable. This process is called Data Cleaning, and it involves fixing issues like missing values. By doing this, we improve the accuracy and trustworthiness of our later analyses.

When we first looked at the data, we noticed something unusual in the "ATAR," "AT2," and "AT3" columns. These columns had some values that were 0, which doesn't make sense given what these columns represent. So, in total, we had 29 missing values, i.e. 17 in “ATAR”,6 in “AT2” and “AT3”. We decided to replace these 0 values with NaN (Not-a-Number) to handle this. This helps us keep the data consistent and prepares us for the next step: removing rows with missing values. This makes the data more accessible without dealing with specific value ranges. After this cleanup, our dataset has 89 rows of cleaner and more accurate information.

5.2.3 Computing Derived Variables

Derived variables are crucial in unveiling new insights from existing data through calculations, transformations, or aggregations. This simplifies analysis and enhances data's applicability for informed decision-making. Building upon this concept, our exploration into the dataset has led us to uncover students' motivational orientations and their leanings towards the Hybrid teaching approach.

This process involved categorizing motivation types by calculating Intrinsic and Extrinsic motivation percentages. This analysis hinged on specific questions tailored to capture these motivational dimensions. To compute the Intrinsic percentage, we aggregated ratings from Intrinsic motivation questions. We divided the sum by 80—a value derived from multiplying 16 (the number of Intrinsic questions) by 5 (the highest possible rating). Similarly, the Extrinsic percentage was established by summing the ratings linked to Extrinsic motivation questions and then dividing the result by 40—a figure stemming from the multiplication of 8 (the number of Extrinsic questions) and 5 (the maximum rating) (Refer to Appendix E for detailed information).

Utilizing these derived percentages, we undertook the task of categorizing students into intrinsic and extrinsic motivation groups. This classification was achieved by implementing a threshold of 50%; students with percentages below 50% were classified as extrinsically motivated. This methodology effectively stratified students based on their motivational tendencies, paving the way for a thorough understanding of their Hybrid teaching preferences.

Building on this foundation, our next step was to derive students' Likeness for Hybrid mode. This involved setting a threshold of 3 for the question, "On balance, the hybrid class is a worthwhile way of teaching." Students with ratings above the median value of

3 responded positively to the Hybrid teaching mode. This comprehensive approach adds depth to our study's insights into student preferences, enriching our analysis and paving the way for a comprehensive understanding of motivation dynamics and teaching preferences.

5.3 DESCRIPTIVE STATISTICS

The below table presents descriptive statistics for nine variables, each based on a sample size of 89 observations. Among these variables, those marked with an asterisk are categorical.

Variable	n	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis	SE
ATAR	89	74.63	17.10	74.00	19.45	99.55	80.10	-0.50	-0.07	1.81
Course Weighted Average	89	74.74	10.75	76.75	32.67	92.00	59.33	-1.63	3.34	1.14
Age	89	21.55	7.21	19.00	18.00	62.00	44.00	3.75	14.67	0.76
IMI Total	89	91.21	13.90	93.00	54.00	122.00	68.00	-0.27	-0.13	1.47
AT2	89	16.17	2.35	17.00	4.00	18.00	14.00	-2.31	7.33	0.25
AT3	89	74.24	13.72	76.00	25.00	97.00	72.00	-0.97	1.34	1.45
IM_Percentage	89	66.66	11.08	67.50	38.75	88.75	50.00	-0.28	-0.46	1.17
EM_Percentage	89	61.74	10.37	65.00	30.00	82.50	52.50	-0.56	0.03	1.10
TOTAL	89	77.84	10.84	79.16	31.56	93.73	62.17	-1.77	4.56	1.15

Table 5.3. 1:Descriptive Statistics for all variables

The "ATAR" variable has an average score of 74.63 with a spread of 17.10, as indicated by its standard deviation. Most scores are clustered around the median of 74.00, with the values ranging from 19.45 to 99.55. Its distribution is slightly negatively skewed and has a kurtosis value close to zero, suggesting a reasonably normal distribution. The "Course Weighted Average" variable presents a mean of 74.74 and a standard deviation 10.75. The scores primarily lie between 32.67 and 92.00. Its negative skewness and positive kurtosis values indicate a left-skewed distribution with a peak. The "Age" variable averages 21.55 years, with a spread of 7.21 years. Most participants are around the median age of 19, but the ages in the sample range from 18 to 62 years. With its high skewness and kurtosis values, the right-skewed and leptokurtic distribution indicates more young participants than older ones. The "IMI Total" variable has a mean score of 91.21 with a standard deviation 13.90. The scores range from 54.00 to 122.00, suggesting a broad spread in intrinsic motivation among the participants. Its distribution is slightly negatively skewed with a kurtosis value near zero.

The mean for the "AT2 article summary Wk 5" variable is 16.17, with scores ranging from 4.00 to 18.00. The negative skewness and high kurtosis values indicate a left-skewed and peaked distribution. The "AT3" variable shows a mean of 74.24 and scores mainly between 25.00 and 97.00. The distribution is slightly left-skewed and platykurtic. The variables "IM_Percentage" and "EM_Percentage" have means of 66.66 and 61.74, respectively. Both have distributions that are slightly left-skewed with kurtosis values near zero.Lastly, the "TOTAL" variable has an average score of 77.84, with most scores between 31.56 and 93.73. Its distribution is negatively skewed with a higher kurtosis value, indicating a left-skewed distribution with a pronounced peak.Overall, these descriptive statistics provide a comprehensive understanding of the distribution and central tendencies of each variable in the dataset.

5.4 Data Pre-processing

The refinement of raw data through preprocessing is pivotal for enhancing the precision of results and the efficacy of models. The techniques employed for the transformation of Categorical and Numerical values include:

5.4.1 Numerical encoding for categorical variables

This technique assigns integer values to categorical data like "1" for category 1," 2" for category 2 and so on.

During the data preprocessing phase, the 'Campus' variable was transformed, leading to the introduction of a binary variable named "Campus_transformed". In this transformation, the "Bundoora" campus was assigned a value of 1, while all other campus locations received a value of 0. Additionally, several categorical variables underwent binary encoding to optimize their compatibility with regression analysis. For the 'Mode' variable, 'Online' was represented as 2 and 'Hybrid' as 1. In the “Motivation_Type” variable, 'INTRINSIC' was encoded as 2 and 'EXTRINSIC' as 1. For the “Like_Hybrid” variable, 'YES' was assigned a value of 2 and 'NO' a value of 1. The “Gender” variable saw Males represented as 0 and Females as 1. This meticulous preprocessing ensures that the dataset aligns seamlessly with the analytical model's assumptions, enhancing the study's precision and clarity.

5.4.2 Transforming Continuous Variables for Modelling

Continuous variables within our dataset exhibited skewness, necessitating transformation to ensure their appropriateness for modelling. Given the data's specific characteristics, we considered various techniques, including logarithmic, square root, and scaling transformations. For our regression analysis, we ultimately chose the logarithmic transformation due to its effectiveness in addressing issues related to non-normality and variance heterogeneity. The "AT3" variable, in particular, underwent this logarithmic transformation to enhance its distribution properties. The subsequent sections will present the data distribution both before and after the transformation, highlighting the improvements achieved through this process.

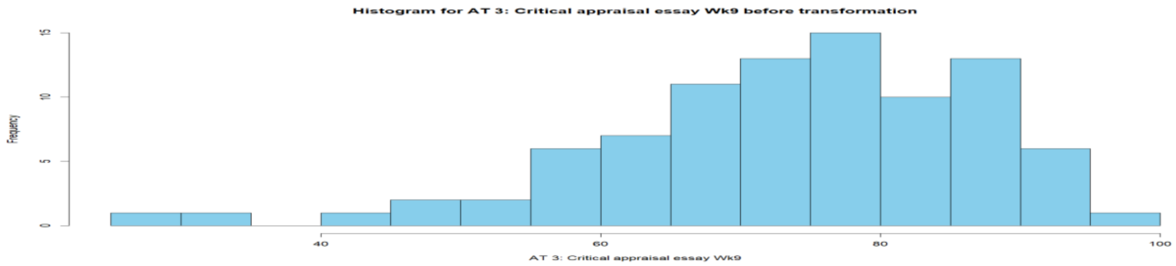


Figure 5.4.2. 1:Before log transformation

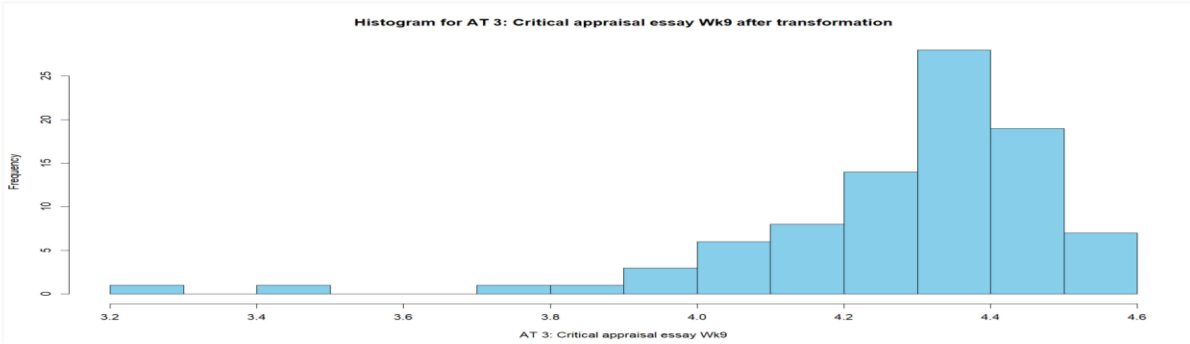


Figure 5.4.2. 2:After log transformation

5.5 Statistical Testing

Statistical tests are essential tools in research, used to make decisions about populations based on sample data. They help determine the validity of a hypothesis, assess relationships between variables, or compare group differences. By employing statistical tests, researchers can ascertain the likelihood that the observed data aligns with a specific hypothesis or if it occurred by random chance.

In this research, the following statistical tests are employed:

- **Shapiro-Wilk Tests:** This test assesses whether a data sample comes from a normally distributed population.
- **Man-Whitney U Test:** A non-parametric test used to compare the medians of two independent samples and when the data doesn't meet the assumptions of a t-test, especially concerning normal distribution.
- **Fisher's Test:** These tests determine if there's a significant association between two categorical variables and used to understand relationships between different groups or categories.

Prior to initiating any statistical testing, we will employ the Shapiro-Wilk test to evaluate the normality of the variable. In cases where the variable deviates from a normal distribution, we will proceed to conduct the Mann-Whitney U test. Consequently, our statistical analysis commences with an examination of whether disparities exist in AT3 grades among students engaged in distinct modes of study. This inquiry seeks to address the question: " ***Is there any differences in grades between students in hybrid and online learning?"*** While we have initially addressed this query through the boxplot visualization presented in Figure 5, we intend to confirm these findings more precisely through statistical testing.

Variable name	Statistical test	p-value	Significant
Mode vs AT3	Mann-Whitney U	0.121	No
Motivation type vs AT3	Mann-Whitney U	0.6842	No
Like Hybrid vs AT3	Mann-Whitney U	0.8816	No
Gender vs AT3	Mann-Whitney U	0.3169	No
Mode vs Motivation Type	Fisher's Exact Test	0.8237	No
Mode vs Like Hybrid ?	Fisher's Exact Test	0.3512	No
Like Hybrid ? vs Motivation Type	Fisher's Exact Test	1	No
Gender vs Motivation Type	Fisher's Exact Test	0.2818	No

Table 5.5. 1:Mann-Whitney U Analysis of AT3 Grades Across Variables.

From our analysis using the Mann-Whitney U test, the data in aboove table suggests no significant difference in AT3 grades based on study mode (p-value: 0.121), motivation type (p-value: 0.6842), hybrid learning preference (p-value: 0.8816), or gender (p-value: 0.3169).Further, when examining associations between categorical variables with the Fisher's Exact Test, we found no substantial associations. Specifically, there was no notable link between study mode and motivation type (p-value: 0.8237), study mode and hybrid preference (p-value: 0.3512), or even hybrid preference and motivation type (p-value: 1). Similarly, the relationship between gender and motivation type was also not significant (p-value: 0.2818).

In essence, the above table reveals that the variables considered don't notably influence AT3 grades or associate significantly with each other.

5.6 DATA MODELLING

In this study, data modelling primarily employs Linear Regression and Regression Trees. Linear regression is a statistical method used to analyse the relationship between a dependent variable and one or more independent variables. Meanwhile, Regression Trees partition the data into subsets to make predictions based on certain decision rules. Both techniques offer valuable insights into the dataset's underlying patterns and relationships.

5.6.1 Regression Assumption Check for Basic Variables

Before proceeding with the regression modelling stage, it is essential to assess whether the dataset adheres to two fundamental assumptions integral to linear regression. These assumptions significantly impact the validity of our model's results.

The first assumption pertains to the linearity between independent variables and the target variable. This assumption posits that changes in the independent variables should exhibit a linear relationship with changes in the target variable. Deviation from this assumption can undermine the model's predictive accuracy and interpretation.

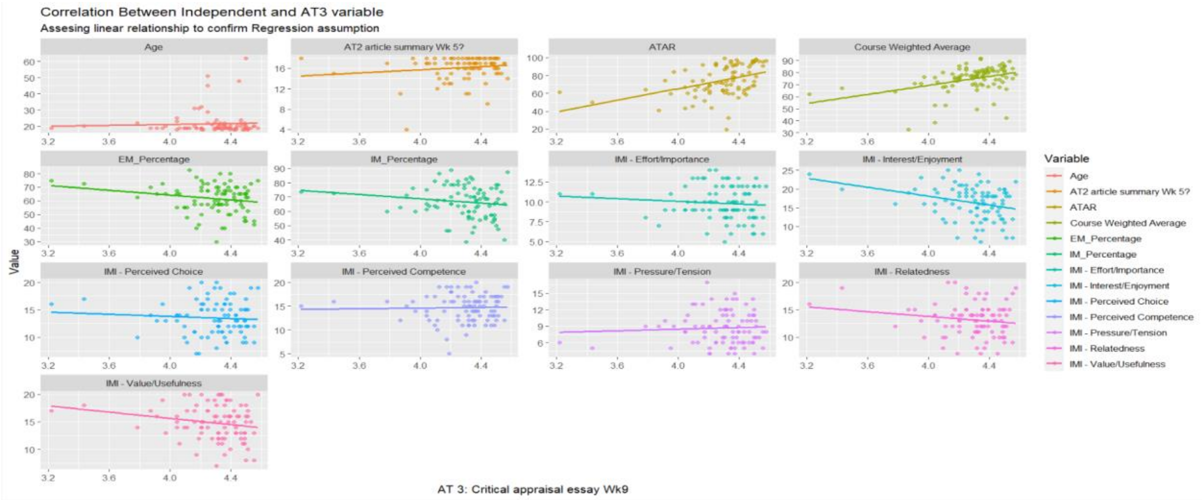


Figure 5.6.1. 1:Asses Linear relationship with AT3_transformed

In the examination of scatterplot grids, we discern several notable relationships between variables.

- **ATAR and AT3_transformed:** A moderately strong, positive linear association is evident between ATAR and AT3, suggesting their interdependence.
- **Course Weighted Average and AT3_transformed:** A substantial positive correlation is observed, indicating that higher Course Weighted Averages tend to correspond with higher AT3 scores.
- **IM_percentage and AT3_transformed:** IM_percentage exhibits a negative linear relationship with AT3, implying that higher intrinsic motivation percentages are associated with lower AT3 scores.
- **Interest/Enjoyment and AT3_transformed:** This variable shows a more pronounced negative linear relationship with AT3, suggesting that as Interest/Enjoyment decreases, AT3 scores tend to increase.
- **IMI-Value/Usefulness and AT3_transformed:** IMI-Value/Usefulness demonstrates a strong negative linear relationship with AT3, indicating that as perceived value and usefulness decrease, AT3 scores tend to rise.

These observations provide valuable insights into how these variables may impact AT3 within our analysis.

The second vital assumption is the absence of multicollinearity among independent variables. Multicollinearity, marked by strong correlations between these variables, can obscure the model's interpretability. This occurs because it becomes difficult to discern the individual effects of each variable on the outcome. Ignoring multicollinearity can result in biased or unreliable model outcomes. Hence, it is crucial to ensure that independent variables do not display high correlations before conducting linear regression analysis.

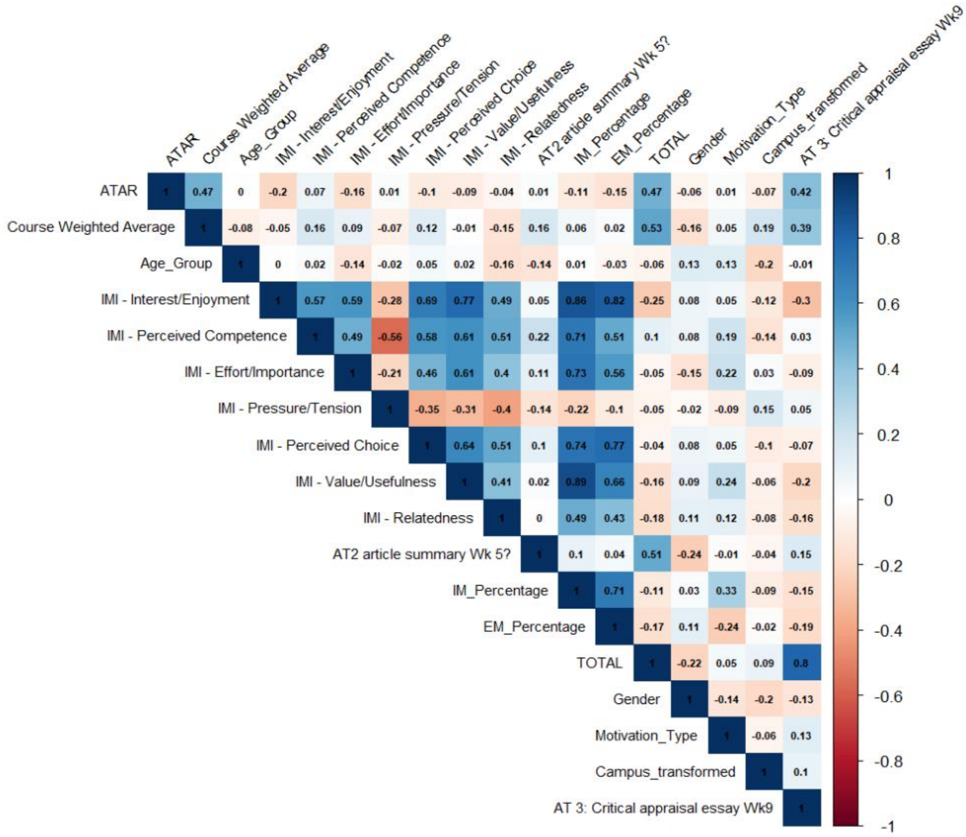


Figure 5.6.1. 2:Correlation Plot between AT3 and Independent Variables to examine multi-collinearity

The correlation plot reveals a noteworthy pattern of multicollinearity among variables associated with the Intrinsic Motivation Inventory (IMI). Specifically, high correlation coefficients are observed between different IMI-Subscales, such as Interest/Enjoyment, and other variables like Perceived Competence, Effort/Importance, Perceived Choice, Value/Usefulness, IM_percentage, and EM_percentage. Such a pattern of multicollinearity could compromise the robustness of a linear regression model by obscuring the unique contributions of individual predictors to the dependent variable. This, in turn, could lead to unreliable and biased estimates. In light of these observations, prudence dictates the consideration of either removing or combining certain correlated variables to mitigate the adverse impact of multicollinearity.

In our pursuit of refining the model, we undertook a systematic approach to address multicollinearity. This process involved the judicious removal of independent variables that exhibited high correlations among themselves. Our strategy emerged from the distinct multicollinearity pattern we observed, primarily among variables linked to the Intrinsic Motivation Inventory (IMI). Notably, robust correlation coefficients were evident between various IMI-Subscales, such as Interest/Enjoyment, and additional variables, including Perceived Competence, Effort/Importance, Perceived Choice, Value/Usefulness, IM_Percentage, and EM_Percentage. This intricate web of multicollinearity raised legitimate concerns regarding the interpretability and stability of our linear regression model, as it had the potential to obscure the distinctive contributions of individual predictors to the dependent variable, potentially leading to unreliable and biased estimates.

In our quest to refine the model, we took a systematic approach to tackle multicollinearity, particularly among variables associated with the Intrinsic Motivation Inventory (IMI). This process involved the deliberate removal of independent variables that exhibited high correlations among themselves. The rationale for this strategy became evident as we examined a pronounced multicollinearity pattern, predominantly among IMI-Subscales. Notably, strong correlation coefficients were found between various IMI-Subscales, such as Interest/Enjoyment, and additional variables, including Perceived Competence, Effort/Importance, Perceived Choice, Value/Usefulness, IM_Percentage, and EM_Percentage.

To address this intricate web of multicollinearity, we strategically removed specific correlated variables from the model. These removals encompassed all IMI-Subscales except Pressure/Tension, as they demonstrated high correlations with IM_Percentage. The rationale was to streamline our model by retaining IM_Percentage, which effectively represents both intrinsic and extrinsic motivation among students. Additionally, we eliminated EM_Percentage (Extrinsic motivation percentage) due to its substantial correlation with IMI-Perceived Choice. This comprehensive selection process was guided by the principle of retaining variables that best capture the essential factors influencing student performance while adhering to the model's integrity.

Following these strategic removals, we re-evaluated our correlation matrix, which now indicates a reduced level of correlation among independent variables. Consequently, we are now confident in the suitability of our selected variables for our linear regression analysis. This transformation aligns with the fundamental assumptions of the model, ultimately enhancing its predictive capabilities.

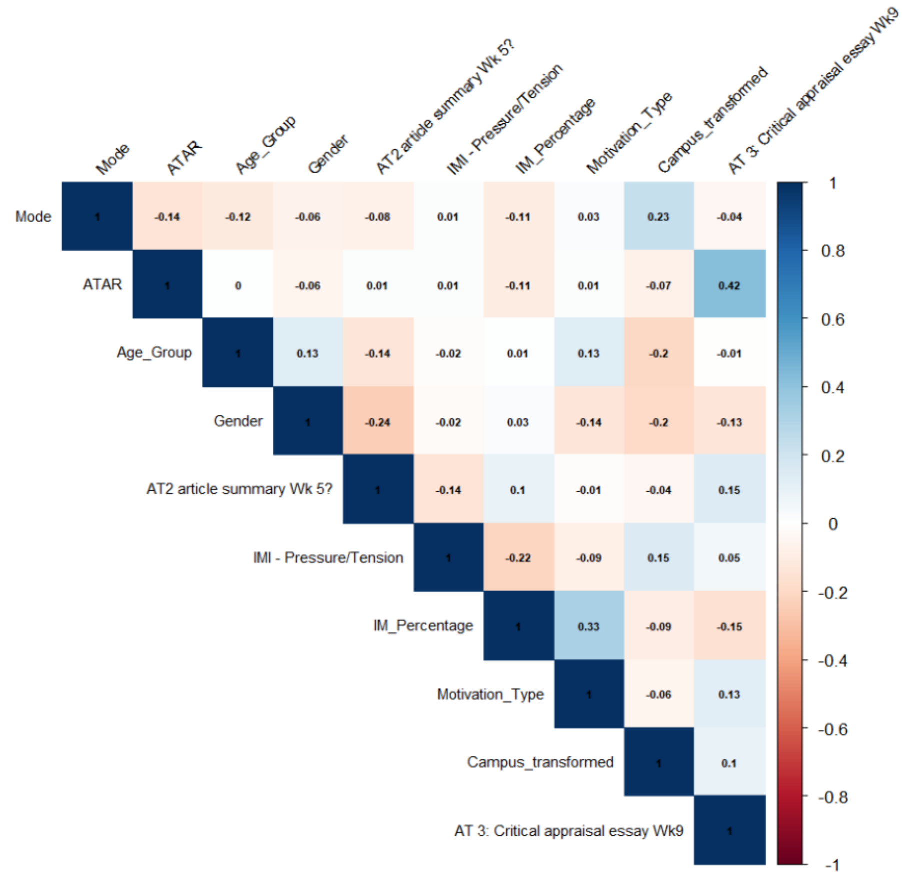


Figure 5.6.1. 3:Correlation Matrix After removing HC Independent variables

5.6.2 Linear regression modelling

This research will use linear regression to predict the AT3 grade performance, considering various factors associated with hybrid teaching and student motivations.

After the preliminary analysis and selection of variables, the independent variables incorporated in the initial regression model for predicting “AT3” include “Mode”,” ATAR”, “Age_Group”, “Gender”, “AT2”, “IM_Percentage”,” Motivation_Type” and “Campus_transformed”. The equation for the above variable is as follows:

$$\begin{aligned} AT\ 3\text{: } Critical\ appraisal\ essay\ Wk9 \\ &= \beta_0 + \beta_1 \times Mode + \beta_2 \times Campus_{transformed} + \beta_3 \times ATAR + \beta_4 \times Age_{Group} \\ &+ \beta_5 \times Gender\ + \beta_6 \times AT2\ article\ summary\ Wk\ 5? + \beta_7 \times IM\_Percentage \\ &+ \beta_8 \times IMI\ -\ Pressure/Tension + \beta_9 \times Motivation\_Type + \epsilon \end{aligned}$$

Equation 5.6.2. 1:Linear Regression formula for hybrid teaching variables

Variable	Estimate	Std_Error	t_value	p_value	95% CI
Mode	0.170	0.070	2.414	0.018	(0.032, 0.308)
ATAR	0.011	0.002	5.846	0.000	(0.007, 0.015)
Age	0.009	0.006	1.636	0.106	(-0.002, 0.020)
Gender	0.261	0.080	3.247	0.002	(0.104, 0.419)
IMI - Pressure/Tension	0.035	0.011	3.138	0.002	(0.013, 0.057)
AT2 article summary Wk 5	0.084	0.013	6.574	0.000	(0.059, 0.109)
IM_Percentage	0.006	0.003	1.689	0.095	(-0.001, 0.012)
Motivation_Type	0.172	0.081	2.108	0.038	(0.012, 0.331)
Campus_transformed	0.189	0.080	2.353	0.021	(0.032, 0.346)
Age_Group	0.153	0.081	1.886	0.063	(-0.006, 0.312)

Table 5.6.2. 1:Baseline Linear Regression Variables

The analysis initiated with a baseline linear regression model to predict "AT 3" incorporating independent variables like Mode, ATAR, Age_group, Gender, "AT2," and Intrinsic Motivation Percentage (IM_Percentage). The model demonstrated superior performance, with Multiple (R^2) and Adjusted (R^2) at 99.48% and 99.42%, respectively, showcasing its efficacy in elucidating the variance in AT 3. A minimal RMSE of 0.31 units underscores the model's precision, indicating a close proximity between actual and predicted values. Variables such as "ATAR", "Gender", "AT2", "IMI – Pressure/Tension", and "Motivation_Type" were deemed statistically significant, emphasizing their pivotal role in augmenting the model's predictive proficiency.

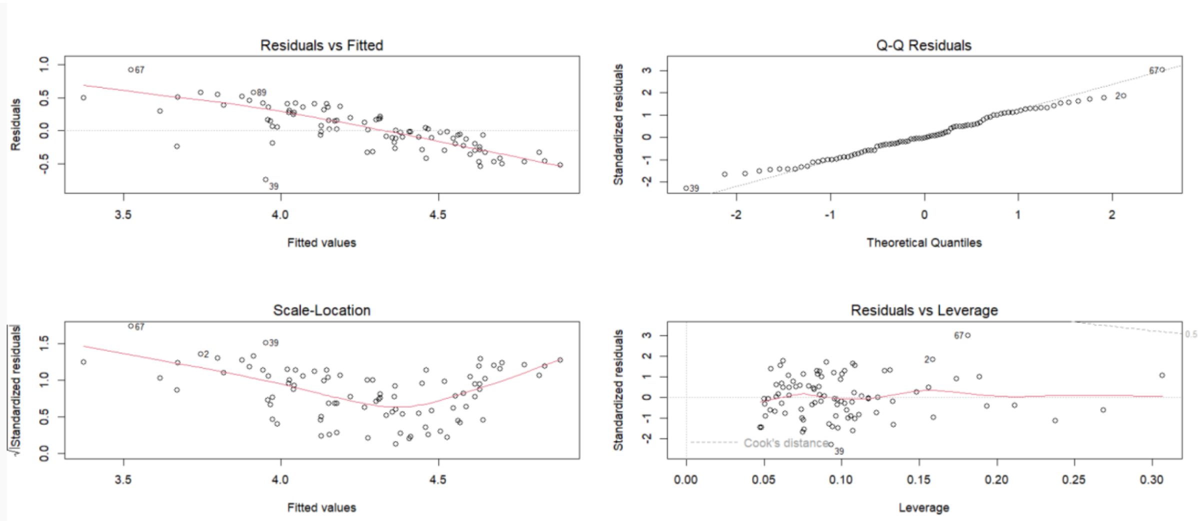


Figure 5.6.2. 1: Diagnostic Plot for baseline linear regression

The Residuals vs. Fitted plot supports these performance measures, showing that the residuals are evenly spread around the zero line. This pattern suggests that the model fits the data well.

In summary, the baseline model shows strong performance and accuracy in its predictions. This is confirmed by high (R^2) values, low Root Mean Square Error (RMSE), and a Residuals vs. Fitted plot that meets the criteria for a well-fitting model.

5.6.2.1 *Variable selection for linear regression using stepwise linear regression modelling*

After the initial baseline regression model was developed, stepwise regression was utilized to enhance it further.

Stepwise regression is a method of fitting regression models in which the choice of predictive variables is carried out by an automatic procedure. In this iterative process, all available variables were initially considered and added or removed based on their statistical significance, represented by their p-values. The objective was to construct a model that is both succinct and possesses high predictive accuracy.

The table below presents the estimated coefficient, standard error, and the p-value of significant predictors in our model. Mode, as explained previously, represents the mode of study of the students (online or hybrid).

Coefficient	Estimate	Std. Error	t value	p-value	95% CI
Mode	0.175	0.071	2.470	0.016	(0.036, 0.314)
ATAR	0.012	0.002	6.071	0.000	(0.008, 0.016)
Gender	0.263	0.082	3.187	0.002	(0.101, 0.425)
IMI - Pressure/Tension	0.036	0.012	3.064	0.003	(0.013, 0.059)
AT2	0.088	0.013	6.952	0.000	(0.063, 0.113)
IM_Percentage	0.008	0.003	2.433	0.017	(0.002, 0.014)
Motivation_Type	0.184	0.083	2.222	0.029	(0.022, 0.347)
Campus_transformed	0.120	0.052	2.320	0.023	(0.019, 0.221)
Age_Group	0.103	0.075	1.370	0.175	(-0.044, 0.250)

Table 5.6.2.1. 1:Stepwise linear regression variables

The results from the stepwise linear regression model was consistent with the baseline regression, suggesting the robustness of the identified predictors. The refined model includes statistically significant variables such as “Mode”, “ATAR”, “Gender”, “IMI–Pressure/Tension”,”AT2”, “IM_Percentage”, “Motivation_Type”, and Campus_transformed. Despite the model's simplification, it maintains a robust fit, evidenced by an Adjusted R-squared value of 99.39% and a Multiple R-squared value of 99.45%. This indicates that the model can account for nearly all the variability in “AT3.” Furthermore, an RMSE of 0.31 underscores the model's precision in predictions. Key predictors like “ATAR”, “Gender”, “IMI – Pressure/Tension”, “AT2”, “Motivation_Type”, and “Campus_transformed” play a pivotal role in explaining the dependent variable and warrant attention in subsequent analyses.

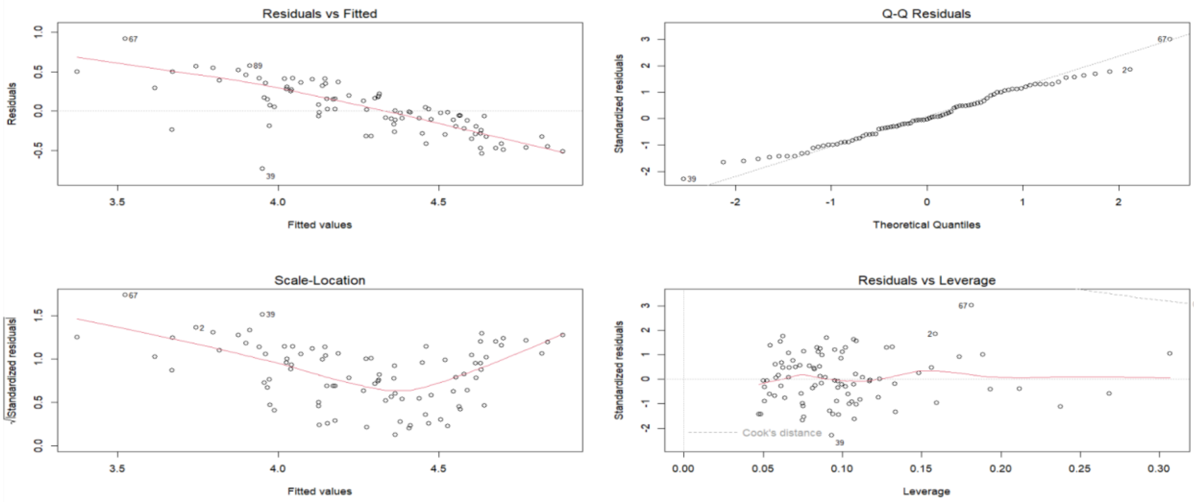


Figure 5.6.2.1. 1:Diagnostic plot for stepwise regression

The plot of Residuals vs. Fitted shows residuals scattered randomly, suggesting the model is likely accurate. They centre around zero, showing a good fit between the model and the data. The model has an RMSE of 0.31, representing the difference between predicted and actual values—a lower value means a better fit. In short, the stepwise regression has created a reliable and effective model, suitable for those needing a clear and dependable model for "AT3".

5.6.2.2 *Variable selection for linear regression using regression tree*

A variable selection was performed using a regression tree approach to refine the predictive model. This approach divides the dataset into subsets based on the values of independent variables, aiming to reduce the sum of squared residuals in each subset. The significant variables affecting this division are deemed essential and are incorporated into an improved linear regression model. According to the regression tree analysis, the refined model includes variables like ATAR, IM_Percentage, AT2 Article Summary (Week 5), IMI - Pressure/Tension, Campus (binary)

Variable	Estimate	Std_Error	t_value	p_value	95% CI
ATAR	0.013	0.002	6.312	0.000	(0.009, 0.018)
IM_Percentage	0.014	0.003	4.665	0.000	(0.008, 0.020)
AT2 article summary Wk 5	0.097	0.014	6.953	0.000	(0.069, 0.124)
IMI - Pressure/Tension	0.048	0.013	3.772	0.000	(0.023, 0.072)
Campus_transformed	0.251	0.084	3.006	0.003	(0.087, 0.415)

Table 5.6.2.2. 1:Linear regression variables selected by regression tree using variable importance.

When comparing the stepwise linear regression model to the regression model informed by the decision tree, we note that "Age_Group" is only present in the stepwise model. Both models consistently highlight the importance of predictors like "ATAR", "IM_Percentage","AT2"," IMI - Pressure/Tension", and "Campus_transformed".

Using the decision tree's predictors, the regression model achieved an Adjusted R-squared of 0.9928 and a Multiple R-squared of 0.9923. These values are slightly lower than the 0.9942 and 0.9948 from the stepwise model, respectively. The tree-based model has an RMSE of 0.37, compared to the stepwise model's RMSE of 0.31, indicating the stepwise model's slightly better fit.

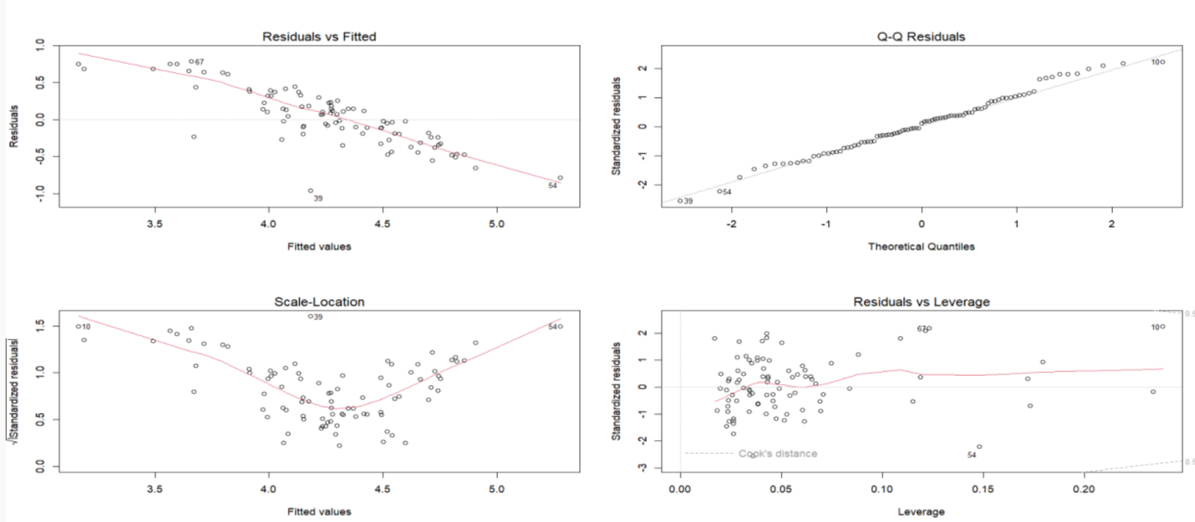


Figure 5.6.2.2. 1:Diagnostic plots for linear regression using regression tree variables

The Residuals vs. Fitted plot reveals a random spread of residuals, suggesting the likely fulfilment of the model's fundamental assumptions. The residuals clustering around the zero line signify a good fit between the model and the data.

In conclusion, both the stepwise and regression tree methods have yielded robust models that aptly explain the data. The convergence on similar variables by both methods reinforces the reliability of the analysis. The random distribution of residuals in the plot and the low RMSE value further attest to the model's accuracy and reliability.

Model	Variables	Adj. R square	RMSE	p-value
Baseline Linear Regression	Mode, ATAR, Age_group, Gender, IMI - Pressure/Tension, AT2, IM_Percentage, Motivation_Type, Campus_transformed	99.42	0.31	< 2.2e-16
Stepwise Regression Model	Mode, ATAR, Age_group, Gender, IMI - Pressure/Tension, AT2, IM_Percentage, Motivation_Type, Campus_transformed	99.42	0.31	< 2.2e-16
Linear Regression (Variables from Reg Tree)	ATAR, IM_Percentage, AT2, IMI - Pressure/Tension, Campus_transformed	99.2	0.37	< 2.2e-16

Table 5.6.2.2. 2: Linear Regression Models

In conclusion, both the 'Baseline Linear Regression' and 'Stepwise Regression Model' performed similarly, achieving an Adjusted R-squared value of 99.42% and an RMSE of 0.31. These values indicate a strong fit and predictive accuracy. On the other hand, the 'Linear Regression' model, based on variables from the regression tree, showed a slightly lower Adjusted R-squared of 99.2% and a higher RMSE of 0.37. Given the consistent performance of the 'Baseline Linear Regression' model, it stands out as a reliable choice for analysing the dependent variable "AT3".

5.6.2.3 *Linear regression using interaction terms*

We further refined our model by adding interaction terms after initially using stepwise linear regression and regression tree methods. Interaction terms help us see how two variables combined can impact the outcome.

Coefficient	Estimate	Std. Error	t value	p-values	95% CI
Mode	0.450	0.164	2.734	0.007	(0.128, 0.774)
Motivation_Type	1.062	0.270	3.923	0.0001	(0.532, 1.594)
ATAR	0.045	0.004	11.106	< 2e-16	(0.037, 0.053)
AT2	0.127	0.028	4.419	3.01e-05	(0.071, 0.184)
Mode:Motivation_Type	-0.268	0.094	-2.842	0.005	(-0.453, -0.083)
Motivation_Type:ATAR	-0.008	0.002	-2.772	0.006	(-0.014, -0.002)
ATAR:AT2	-0.001	0.0003	-4.002	0.0001	(-0.002, -0.001)

Figure 5.6.2.3. 1: Linear regression using interaction terms

Notably, interactions between "Mode:Motivation_Type", "Motivation_Type:ATAR", and "ATAR:AT2" were significant. The model explained about 99.78% of the outcome's variance and had an RMSE of 0.201, suggesting it's a reliable predictor for the dependent variable, "AT 3".

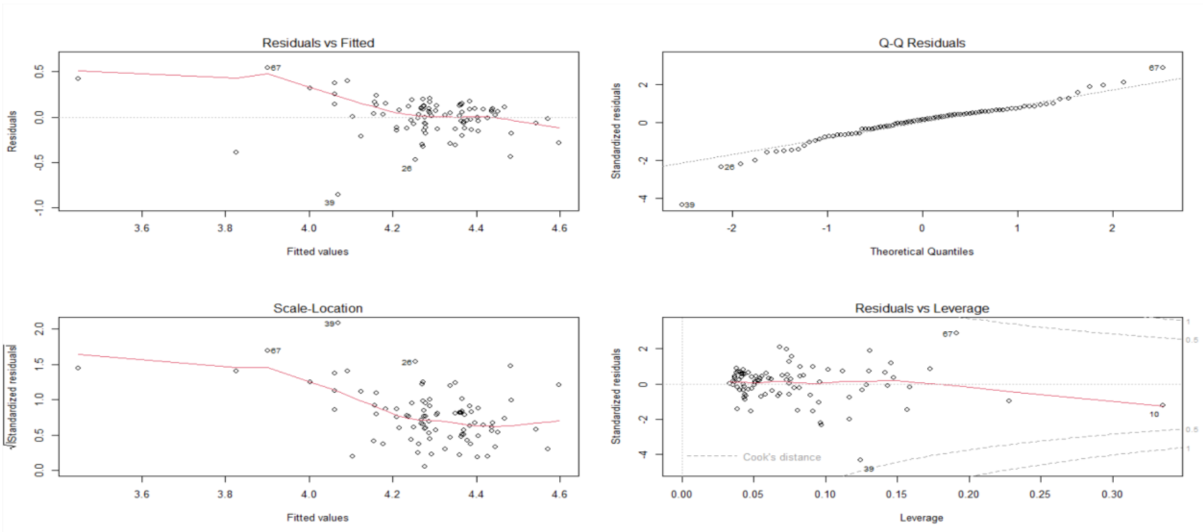


Figure 5.6.2.3. 2:Diagnostic plot for interaction terms in linear regression

The Residuals vs. Fitted plot displays a seemingly random distribution of residuals around the zero line, indicating that the model's primary assumptions are likely met. This random scattering suggests that the model captures the underlying relationships in the data effectively.

In summary, the incorporation of interaction terms in the linear regression model has produced a robust representation of the data. The absence of discernible patterns in the Residuals vs. Fitted plot, combined with the previously mentioned low RMSE of 0.2, underscores the model's precision and trustworthiness.

5.6.2.4 *Linear regression for Hybrid mode including all variables*

Variable	Estimate	Std. Error	t value	p-value	CI (LB, UB)
ATAR	0.012	0.003	4.864	2.14e-05	(0.007, 0.017)
Age	0.005	0.007	0.764	0.450	(-0.008, 0.018)
Gender	0.310	0.100	3.103	0.004	(0.114, 0.506)
IMI - Pressure/Tension	0.023	0.014	1.619	0.114	(-0.005, 0.052)
AT2	0.107	0.021	5.120	9.73e-06	(0.066, 0.148)
IM_Percentage	-0.002	0.005	-0.365	0.717	(-0.011, 0.007)
Motivation_Type	0.293	0.110	2.666	0.011	(0.078, 0.509)
Campus_transformed	0.260	0.131	1.986	0.055 .	(0.003, 0.516)
Age_Group	0.303	0.106	2.858	0.007	(0.095, 0.511)

Figure 5.6.2.4. 1:Linear regression for Hybrid Mode including all variables

In the Hybrid mode dataset regression, the model exhibits robust explanatory power, with an R-squared of 99.62% and an adjusted R-squared of 99.53%, indicating a near-complete account of the variance in "AT3" scores. The model surpasses the baseline regression, which had an RMSE of 0.31 and an adjusted R-squared of 99.42%, demonstrating enhanced precision and fit with a lower RMSE of 0.2639. The similarity of the multiple R-squared value of the baseline (99.48%) to the R-squared of the Hybrid mode indicates a comparable explanatory complexity. A thorough comparison necessitates evaluating the statistical significance of predictors in both models, which, for the baseline, are delineated by a p-value threshold of less than 0.05.

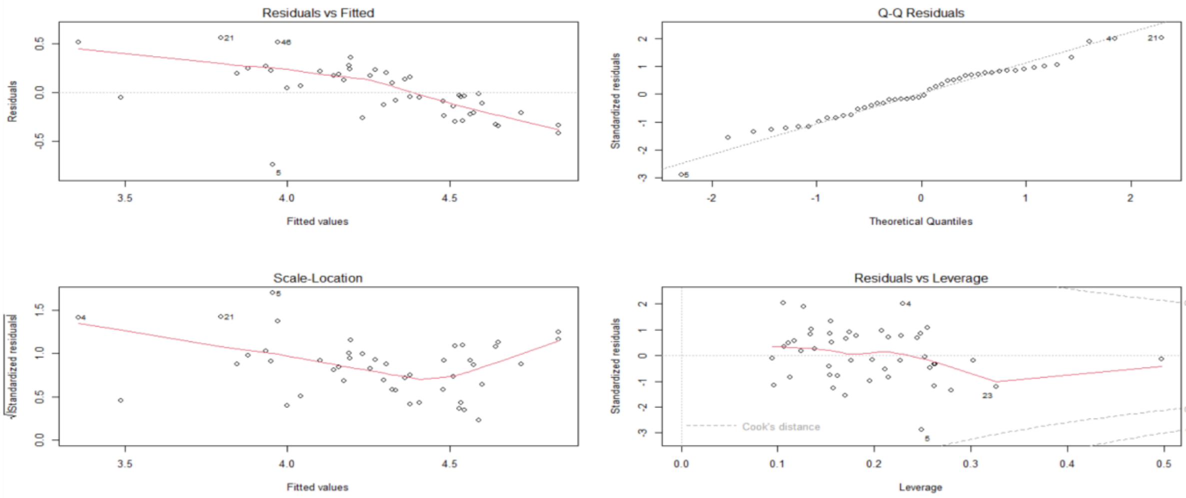


Figure 5.6.2.4. 2: Diagnostic plot for Linear regression for Hybrid mode including all variables

The "Residuals vs. Fitted" plot indicates a subtle non-linear trend, as denoted by the red line's slight curvature. There's a mild increase in the spread of residuals from left to right, suggesting potential heteroscedasticity. No major outliers are evident, and residuals appear independent. Overall, the data may benefit from further transformations or alternative modelling to address the hinted non-linearity and variance inconsistency.

5.6.2.5 *Linear regression for Online mode including all variables*

Variable	Estimate	Std. Error	t value	p-values	95% CI (LB, UB)
ATAR	0.011	0.003	3.572	0.001	(0.005, 0.017)
Age	0.021	0.012	1.714	0.096	(-0.003, 0.045)
Gender	0.226	0.132	1.711	0.096	(-0.033, 0.484)
IMI - Pressure/Tension	0.036	0.019	1.835	0.075	(-0.002, 0.074)
AT2	0.072	0.017	4.262	0.000	(0.039, 0.106)
IM_Percentage	0.012	0.005	2.472	0.019	(0.002, 0.021)
Motivation_Type	0.152	0.124	1.218	0.232	(-0.092, 0.395)
Campus_transformed	0.214	0.109	1.969	0.057	(0.001, 0.427)
Age_Group	-0.025	0.132	-0.192	0.849	(-0.284, 0.233)

Table 5.6.2.5. 1:Linear regression for online mode including all variable

In an examination of the Mode=Hybrid dataset through regression analysis, we observe that the model achieves a high degree of predictive accuracy, denoted by an R-squared of 99.62%, an adjusted R-squared of 99.53%, and an RMSE of 0.2639. Comparatively, the Mode=Online model presents slightly less precision, with an R-squared of 99.46%, an adjusted R-squared of 99.32%, and an RMSE of 0.4019. This comparative analysis suggests that the Mode=Hybrid model slightly outperforms the Mode=Online model in terms of both fit and predictive capacity.

The notable differences in significant variables between the two modes underscore the distinct influences at play within each learning environment. Specifically, in the Mode=Hybrid, variables such as ATAR, Gender, performance in early assessments (AT2 article summary from week 5), Motivation_Type, and Age_Group emerge as significant. These findings suggest that in a hybrid learning context, a student's academic preparedness, gender dynamics, early academic performance, motivational strategies, and age are more predictive of educational outcomes. This may reflect the hybrid environment's unique blend of autonomous and structured learning experiences, where personal attributes and early engagement with the course material play critical roles. Conversely, variables like Age, IMI - Pressure/Tension, and IM_Percentage do not show significance, potentially indicating that the hybrid format's specific demands may not amplify the influence of these factors as they would in an entirely online setting.

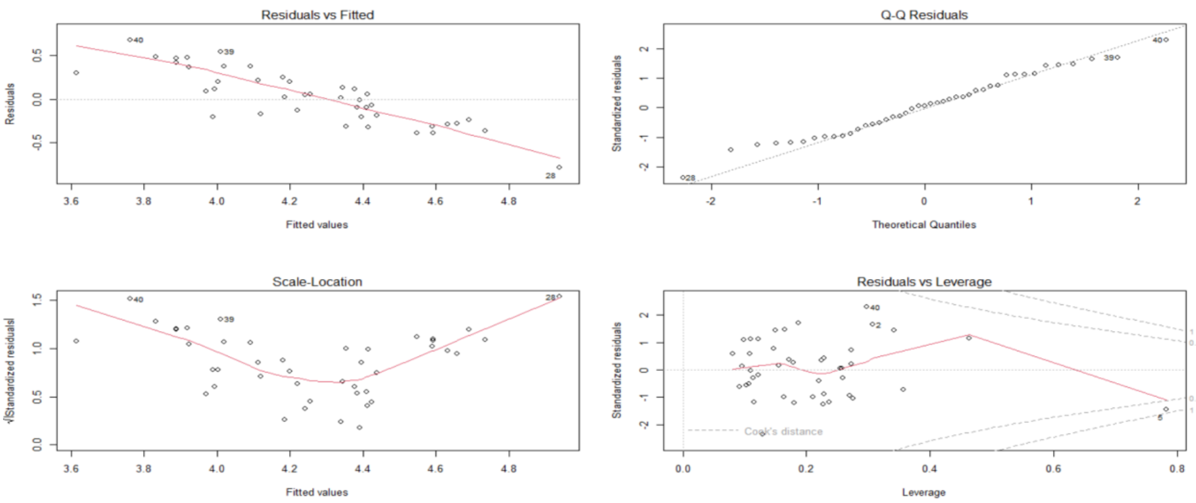


Figure 5.6.2.5. 1: Diagnostoc plot for linear regression for online mode including all variable

The given "Residuals vs. Fitted" plot showcases a slight non-linear trend, as suggested by the red line's curvature. The residuals seem relatively evenly dispersed around the zero line, with no apparent patterns or clusters. No significant outliers are observable. The minor curvature suggests there may still be some non-linear relationship not captured by the model.

5.6.2.6 *Linear regression With AT2 and AT3*

Variable	Estimate	Std. Error	t value	p-value	95% CI
AT2	0.259	0.004	64.26	<2e-16	(0.252,0.267)

Table 5.6.2.6. 1: Linear regression With AT2 and AT3

Comparing significant variables across baseline, Hybrid, and Online modes, we find distinct predictors of student performance. The Hybrid mode emphasizes the importance of academic background (ATAR), gender, initial coursework engagement ("AT2 article summary Wk 5"), motivation, and age demographics. These factors suggest that the Hybrid environment benefits from a mix of individual attributes and early performance. In contrast, the Online mode may prioritize different variables, perhaps due to its reliance on self-directed learning and digital engagement.

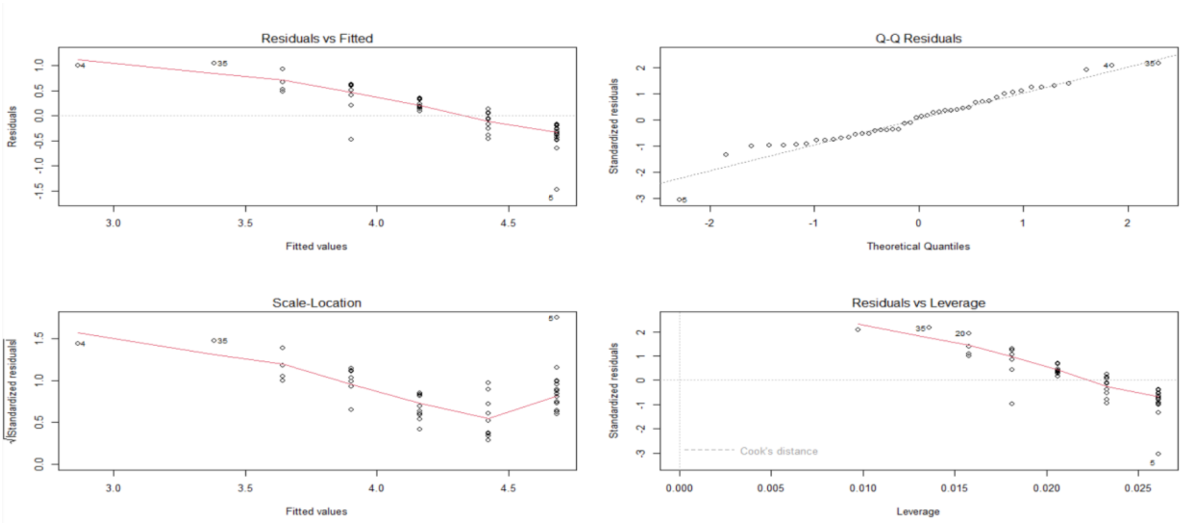


Figure 5.6.2.6. 1: Diagnostic plot for Linear regression With AT2 and AT3

The "Residuals vs. Fitted" plot hints at potential non-linearity, evidenced by the slight curvature in the red line, suggesting the linear model may not fully encapsulate the data's patterns. There's a mild indication of heteroscedasticity, with residuals appearing more dispersed on the right side. A few distant points suggest possible outliers. Overall, while the residuals largely appear random, the model might benefit from data transformations or alternative modelling approaches to address the observed non-linearity.

5.6.2.7 *Linear regression for AT2 and At3 Online Mode*

Variable	Estimate	Std. Error	t value	p-values	95% CI (LB, UB)
AT2	0.260	0.007	36.970	< 2e-16	(0.246, 0.273)

Table 5.6.2.7. 1: Linear regression for AT2 and At3 Online Mode

For the overall dataset, the regression model has an R-squared of 0.9791, an adjusted R-squared of 0.9789, and an RMSE of 0.62. In contrast, for the online mode subset, the R-squared is 0.9702, the adjusted R-squared is 0.9695, and the RMSE is 0.7389. While both models demonstrate strong explanatory power, the overall dataset model slightly outperforms the online mode-specific model in terms of fit and prediction accuracy.

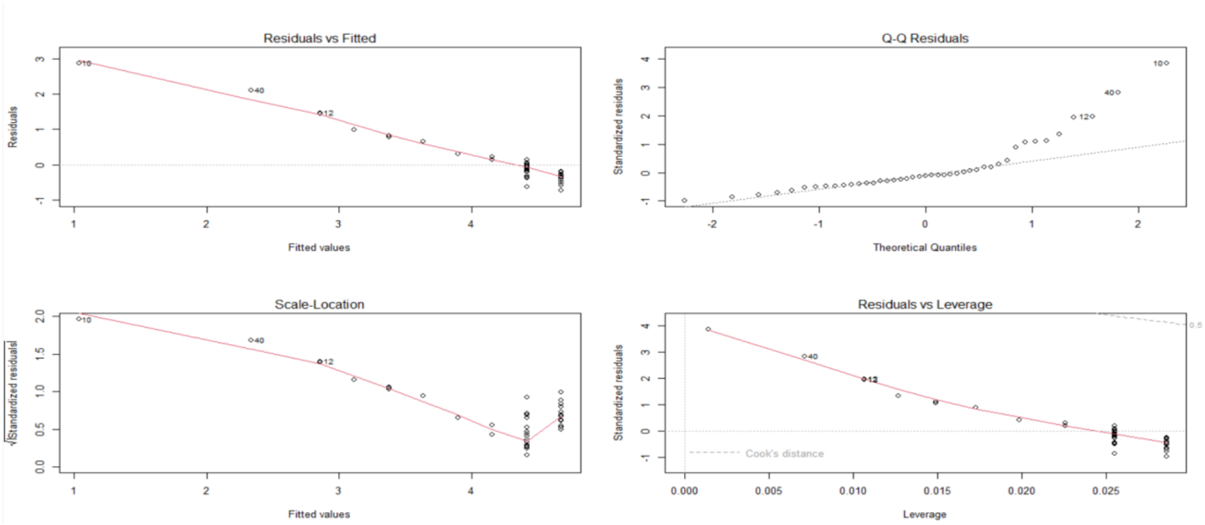


Figure 5.6.2.7. 1: Diagnostic plot for Linear regression for AT2 and At3 Online Mode

The "Residuals vs. Fitted" plot reveals a pronounced downward curvature in the red line, signifying non-linearity in the data, which indicates that the current linear model might not be optimal. The variance of the residuals seems inconsistent, hinting at potential heteroscedasticity. Despite this, there are no significant outliers and the residuals largely appear independent. Overall, the data might benefit from transformations or a non-linear modelling approach.

5.6.2.8 *Linear regression for AT2 and AT3 for Hybrid Mode*

Variable	Estimate	Std. Error	t value	p-values	95% CI (LB, UB)
AT2	0.260	0.004	59.410	< 2e-16	(0.252, 0.269)

Table 5.6.2.8. 1: Linear regression for AT2 and AT3 for Hybrid Mode

The model for Mode "Hybrid" boasts a strong explanatory power, with an (R^2) of 0.9874, indicating it explains roughly 98.74% of the variance in the response variable. When compared to the previous model, this would suggest whether the "Hybrid" mode offers a superior or inferior fit. The Adjusted (R^2) stands close at 0.9871, offering further insight into the model's robustness after accounting for predictors. Meanwhile, the RMSE value of 0.4828 gauges the model's accuracy; a comparison with the previous model's RMSE would determine which provides tighter predictions.

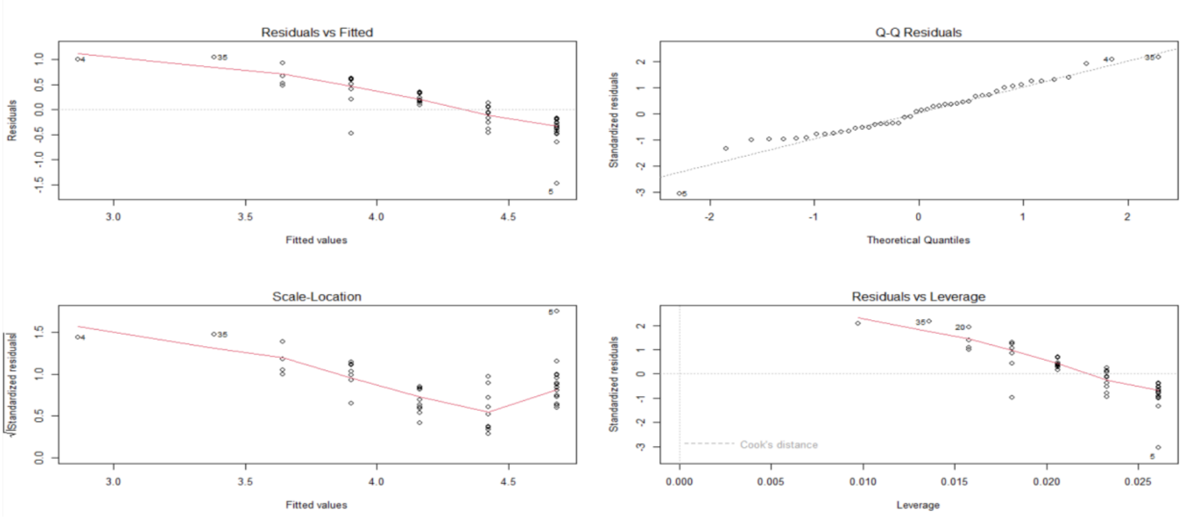


Figure 5.6.2.8. 1 Linear regression for AT2 and AT3 for Hybrid Mode

The "Residuals vs. Fitted" plot hints at potential non-linearity, evidenced by the slight curvature in the red line, suggesting the linear model may not fully encapsulate the data's patterns. There's a mild indication of heteroscedasticity, with residuals appearing more dispersed on the right side. A few distant points suggest possible outliers. Overall, while the residuals largely appear random, the model might benefit from data transformations or alternative modelling approaches to address the observed non-linearity.

5.6.2.9 *Linear regression for AT2-AT3 for all variables*

Variable	Estimate	Std. Error	t value	p-values	95% CI (LB, UB)
Mode	0.009	0.021	0.432	0.667	(-0.033, 0.051)
ATAR	0.000	0.001	0.046	0.963	(-0.001, 0.001)
Age	-0.001	0.002	-0.702	0.485	(-0.004, 0.002)
Gender	0.054	0.025	2.170	0.033	(0.005, 0.103)
IMI - Pressure/Tension	0.004	0.003	1.019	0.311	(-0.003, 0.010)
IM_Percentage	-0.000	0.001	-0.234	0.816	(-0.002, 0.002)
Motivation_Type	-0.009	0.025	-0.349	0.728	(-0.058, 0.040)
Campus_transformed	0.017	0.025	0.700	0.486	(-0.031, 0.066)
Age_Group	0.020	0.025	0.785	0.435	(-0.029, 0.068)

Table 5.6.2.9. 1:Linear regression for AT2-AT3 for all variables

In the regression analysis focusing on the difference between standardized `AT3` and `AT2` scores, the model's performance appears diminished. Specifically, when considering the difference, the adjusted R-squared drops to 0.4534. This is a stark contrast to models without the difference, which boasted an impressive R-squared of 99.38%. Additionally, the RMSE for the difference model is 0.0961, which, while lower, compares to an RMSE of 0.32 in the non-difference models. In essence, the model's ability to explain variance is considerably reduced when targeting the difference between the standardized scores.

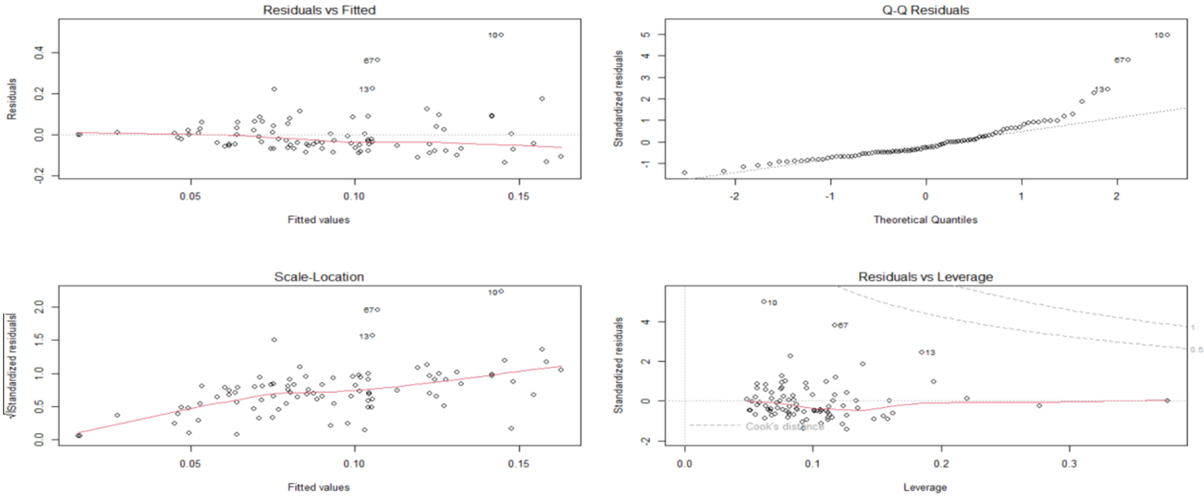


Figure 5.6.2.9. 1: Linear regression for AT2-AT3 for all variables

The "Residuals vs. Fitted" plot exhibits a slight funnel shape, suggesting potential heteroscedasticity. This indicates that the variance of the residuals might not be constant across all levels of fitted values. As the fitted values increase, the spread of the residuals appears to widen. This suggests that the current model might not fully capture the underlying variance structure.

5.6.2.10 *Linear regression for AT2-AT3 for Mode as Hybrid*

Variable	Estimate	Std. Error	t value	p-values	95% CI (LB, UB)
ATAR	-0.000	0.000	-0.179	0.858	(-0.001, 0.001)
Age	0.000	0.001	0.024	0.981	(-0.003, 0.003)
Gender	0.040	0.021	1.872	0.069	(-0.002, 0.081)
IMI - Pressure/Tension	-0.001	0.003	-0.384	0.703	(-0.007, 0.005)
IM_Percentage	0.001	0.001	1.298	0.202	(-0.001, 0.003)
Motivation_Type	-0.023	0.024	-0.957	0.345	(-0.069, 0.024)
Campus_transformed	-0.019	0.028	-0.689	0.495	(-0.073, 0.035)
Age_Group	0.047	0.023	2.091	0.043	(0.003, 0.092)

Table 5.6.2.10. 1: Linear regression for AT2-AT3 for Mode as Hybrid

For the Mode=Hybrid dataset, when examining the difference between standardized AT3 and AT2 scores, the regression model yields an adjusted R-squared of 0.6564. This suggests that the model accounts for approximately 65.64% of the variance in the difference between the standardized scores. The model's prediction accuracy, as indicated by the RMSE, is 0.0574, which is relatively low, suggesting a good fit. Among the predictors, only the Age_Group variable emerged as statistically significant at the 0.05 level. In essence, while the model provides insights into the factors influencing the difference between standardized scores for the hybrid mode, its explanatory power is notably reduced compared to models that consider the scores directly.

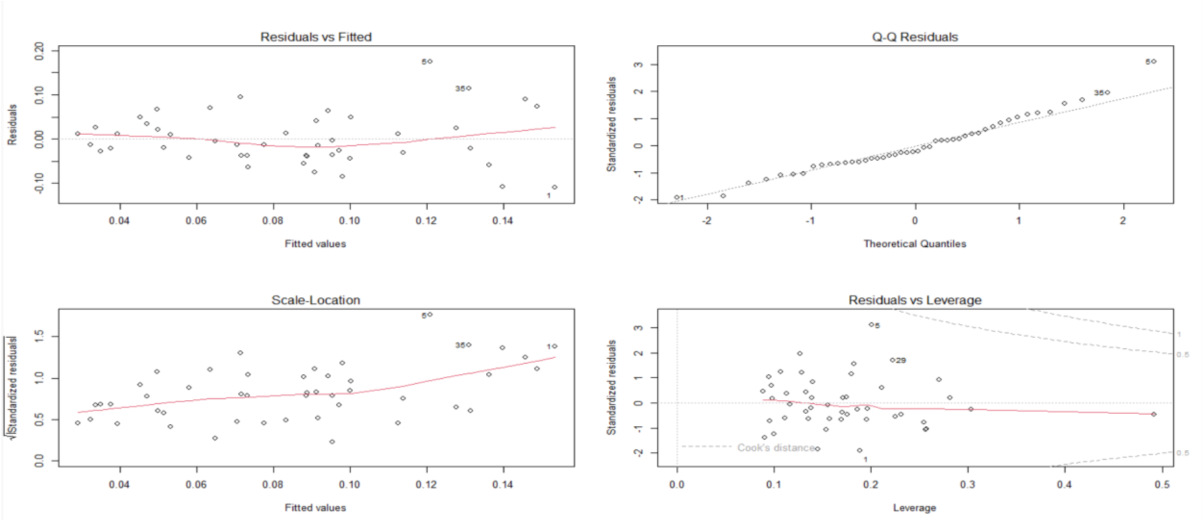


Figure 5.6.2.10. 1:Diagnostic plot for Linear regression for AT2-AT3 for Mode as Hybrid

The "Residuals vs. Fitted" plot presented shows that the residuals are mostly scattered around the zero line, indicating a good fit for most data points. However, there are a few noticeable outliers, specifically the points labeled "50" and "350". The absence of any distinct pattern or funnel shape suggests that the assumptions of linearity and homoscedasticity are largely met. Nevertheless, the presence of these outliers might influence the model's accuracy, so further investigation or potential remediation may be warranted for them.

5.6.2.11 *Linear regression for AT2-AT3 for Mode as Online*

Variable	Estimate	Std. Error	t value	pvalues	95% CI (LB, UB)
ATAR	0.000	0.001	0.151	0.881	(-0.002, 0.002)
Age	-0.004	0.004	-0.938	0.355	(-0.012, 0.004)
Gender	0.055	0.049	1.108	0.275	(-0.042, 0.151)
IMI - Pressure/Tension	0.011	0.007	1.537	0.133	(-0.003, 0.025)
IM_Percentage	-0.000	0.002	-0.164	0.871	(-0.003, 0.003)
Motivation_Type	-0.007	0.046	-0.160	0.874	(-0.098, 0.083)
Campus_transformed	0.025	0.041	0.608	0.547	(-0.055, 0.104)
Age_Group	0.007	0.049	0.149	0.882	(-0.089, 0.104)

Table 5.6.2.11. 1:Diagnostic plot for Linear regression for AT2-AT3 for Mode as Online

In the regression analysis of the `Mode=Online` dataset, targeting the difference between standardized `AT3` and `AT2` scores, the model exhibits an adjusted R-squared of 0.3373. This suggests it accounts for approximately 33.73% of the variance in the difference between the standardized scores. The model's prediction accuracy, denoted by an RMSE of 0.1350, indicates a moderate fit. Notably, none of the predictors are statistically significant at the conventional

0.05 level, implying that while they may influence the difference in scores, their impact isn't robustly established in this context.

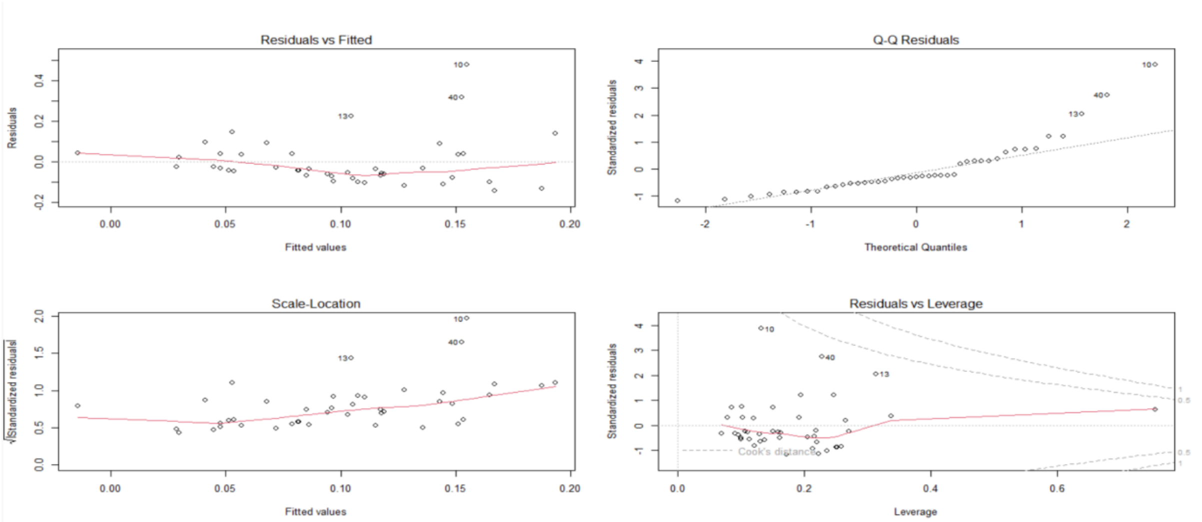


Figure 5.6.2.11. 1:Diagnostic plot for Linear regression for AT2-AT3 for Mode as Online

The displayed "Residuals vs. Fitted" plot illustrates that the residuals predominantly cluster around the zero line, signifying a decent fit for a majority of the data points. However, there are a few standout outliers, specifically the points labeled "100," "130," and "400." The general scatter of the residuals, without a discernible funnel or pattern, suggests that the model reasonably adheres to the assumptions of linearity and homoscedasticity. Yet, the presence of the aforementioned outliers could impact the model's precision and might necessitate further examination or potential adjustments.

5.6.3 Decision tree regression modelling

A careful examination of Linear Regression models reveals their inherent limitations, particularly when confronted with complex, non-linear relationships between variables. In response to these limitations, Decision Tree Regression emerges as a compelling alternative. It excels in identifying intricate, non-linear associations between variables—a capacity notably absent in Linear Regression, which primarily assumes linear relationships. Decision Tree Regression achieves this by segmenting the dataset into smaller subsets based on specific criteria, resulting in a hierarchical 'tree' structure. At the core of this tree structure lies the "Root Node," representing the entire dataset and serving as the initial point for branching.

The first split occurs based on the values of the "Campus_transformed" variable. The "Branches" consist of decision rules or conditions that guide dataset partitioning. In our study, these branches encompass conditions such as "ATAR < 65," "AT2 < 15," "IMI_Percentage ≥ 59," and "IMI - Pressure/Tension ≥ 8," creating distinct pathways within the tree. The "Leaf Nodes" are the terminal points that provide final predictions for the outcome variable. They are represented by specific outcomes and their associated prevalence percentages, such as "4.1" with a prevalence of 20%, "4.3" with 10%, and so on. These designations signify the ultimate model predictions.

Our criteria for selecting the optimal model were guided by achieving the lowest cross-validation error (xerror) while maintaining a minimum split size of 1. While the root mean square error (RMSE) helps assess model fit, Decision Tree Regression excels in predicting new datasets due to its ability to capture complex relationships. In essence, Decision Tree Regression significantly enhances predictive capabilities, making it a valuable analytical tool, particularly when dealing with intricate, non-linear associations between variables—a quality that Linear Regression lacks.

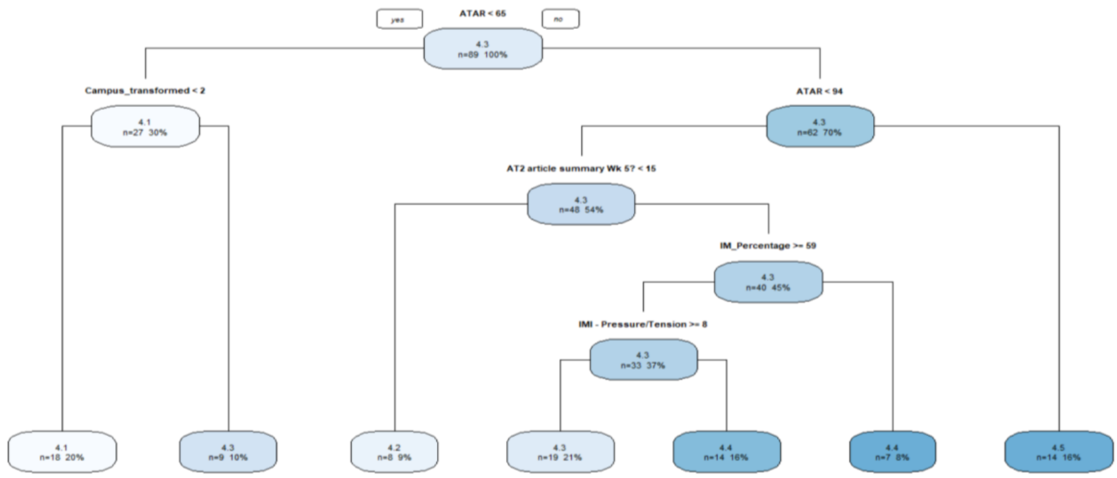


Figure 5.6.3. 1:Baseline regression tree

The provided decision tree offers a visual representation of decision-making based on certain evaluative variables, progressing hierarchically from one decision point to another. Beginning with the "Campus_transformed < 2" criterion, if this is met, it results in an outcome of "4.1" with a prevalence of 20%. However, if not satisfied, the evaluation proceeds to consider the ATAR score. Here, individuals with an ATAR score less than 65 achieve an outcome of "4.3" with a 100% prevalence. For those with an ATAR score ranging from 65 to below 94, another layer of assessment is incorporated based on the "AT2 < 15" criterion. Satisfying this results in an outcome of "4.3" with a 54% prevalence. If this is not met, the "IMI_Percentage" becomes the deciding factor. Those with an IMI_Percentage below 59 achieve an outcome of "4.3" with a 45% prevalence, while those with higher percentages are further evaluated based on "IMI - Pressure/Tension." Specifically, if this value is below 8, the outcome is "4.3" with a 21% prevalence. Conversely, values of 8 or higher lead to two potential outcomes: "4.4" with an 8% prevalence and "4.5" with a 16% prevalence. This decision tree effectively captures the interconnected relationships between variables, such as Campus_transformed, ATAR score, AT2 article summary, IMI_Percentage, and IMI - Pressure/Tension, and provides insight into the consequential outcomes.

In our study, the initial regression tree model provided a clear depiction of how variables interacted and influenced outcomes. To refine its predictive accuracy, we employed the 'cp parameter' for pruning, removing branches that contributed less. This approach, different from linear regression's emphasis on fit, streamlined the tree model, making it more concise and appropriate for insightful predictions.

CP	nsplit	rel error	xerror	xstd
0.1795842	0	1.0000000	1.0159609	0.3155403
0.0783683	1	0.8204158	1.0362074	0.3203460
0.0616698	2	0.7420475	1.0774047	0.3103581
0.0243985	3	0.6803777	0.9911233	0.2933066
0.0165651	4	0.6559792	1.0594769	0.3170715
0.0100000	6	0.6228491	1.0518230	0.3143715

Table 5.6.3. 1:Complexity parameter table for regression tree

The table above, created with the rpart package in R using Decision tree regression, displays metrics including “cp” value, number of splits (“nsplit”), relative error (“rel error”), cross-validation error (“xerror”), and the standard error of “xerror” (“xstd”). A “cp” value of 0.078368 was chosen as optimal for minimizing errors after reviewing the table. Pruning the tree with this “cp” value refined the insights and lowered the RMSE to 0.190. Specifically, the pruned tree showed a 70% probability of a rise in AT3 grades for students with ATAR scores below 65. This refined tree structure underscores the importance of model refinement in deriving accurate and actionable insights.

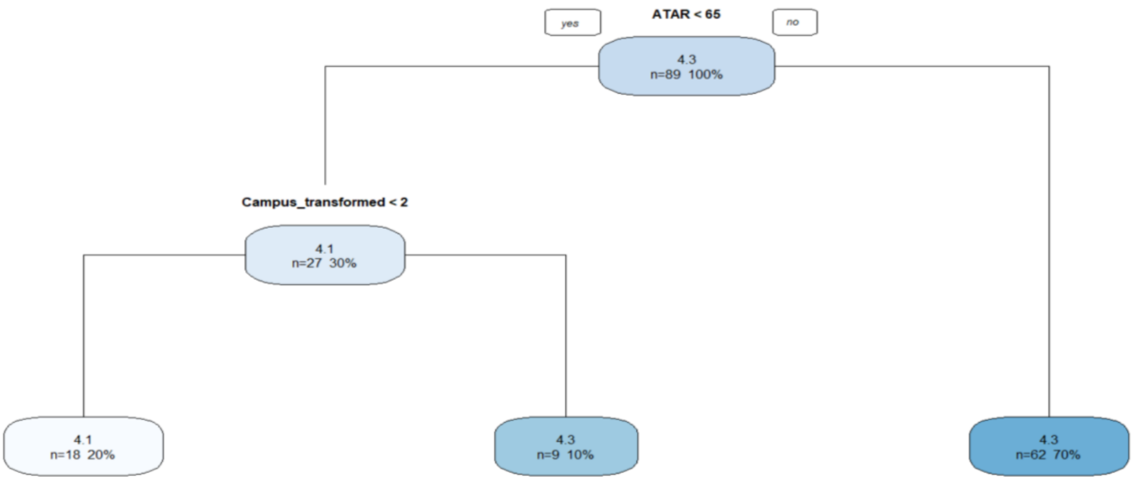


Figure 5.6.3. 2:Pruned Regression Tree

Model	RMSE	Adj.Rsq
Baseline Decision Tree Regression	0.174	56.97
Pruned Decision Tree Regression	0.190	70.57

Table 5.6.3. 2:Decision Tree Regression Results

In summary, the Pruned Decision Tree Regression model demonstrates superior performance in capturing the data's underlying patterns compared to the Baseline Decision Tree Regression model.

5.6.4 Support Vector Machine(SVM) regression

Support Vector Machine (SVM) regression, a machine learning technique renowned for its effectiveness in both classification and regression tasks, was utilized in a recent analysis to predict 'AT3: Critical appraisal essay Wk9' grades. This application of SVM regression exemplifies its versatility in handling various types of predictive modeling problems. In this specific instance, the SVM model was configured with an epsilon-type regression (`eps-regression`), employing a linear kernel to model the relationship between the predictors and the target variable, 'AT3' grades.

5.6.4.1 *Linear kernel*

In an academic study, SVM regression with a linear kernel was employed to predict 'AT3: Critical appraisal essay Wk9' grades, highlighting the model's tailored approach through carefully chosen parameters. The linear kernel assumption suggested a direct linear relationship between the features and the target variable, crucially influencing the model's interpretation and fitting of the data. Key parameters such as the cost of constraints violation `C` and the epsilon in the loss function `epsilon` were precisely calibrated to enhance the model's generalization and predictive accuracy. The model's efficacy was underscored by achieving an RMSE (Root Mean Squared Error) of 0.203, reflecting high precision and reliability in grade prediction. With 81 support vectors contributing to the model, this analysis exemplifies the potential of SVM regression in educational settings, demonstrating its adaptability and effectiveness in accurately predicting academic outcomes.

5.6.4.2 *Radial Basis Function(RBF) kernel*

In a recent analytical study, Support Vector Machine (SVM) regression was adeptly applied to predict 'AT3: Critical appraisal essay Wk9' grades, showcasing the method's robustness in regression tasks. This specific model employed the Radial Basis Function (RBF) kernel, renowned for its efficacy in capturing complex, non-linear data relationships. The optimal model parameters were meticulously determined through hyperparameter tuning, where a range of gamma values, spanning from 10^3 to 10^2, were systematically evaluated. The best-performing model was characterized by an 'eps-regression' type, indicating its focus on epsilon-SVM regression. It utilized a radial kernel, with a cost parameter set to 1, balancing training error tolerance against margin strictness. The gamma parameter, pivotal in defining the kernel's influence, was finely tuned to 0.1. This configuration underscored the model's calibrated approach to managing the trade-offs inherent in SVM regression. The model's effectiveness was further evidenced by an RMSE (Root Mean Squared Error) of 0.164, demonstrating a high level of precision in its predictions. Additionally, the model employed 77 support vectors, reflecting its reliance on these key data points to construct the predictive model.

5.6.5 Moderator analysis for linear regression

Moderator Analysis helps us understand how the relationship between two things, like grades and scores, might change when a third factor, like motivation, comes into play. In simpler terms, it's like seeing if having a different level of interest or enjoyment can change the way scores relate to grades. In this study, we looked at how ATAR scores and

AT3 grades are related and checked if different aspects of motivation, measured by the Intrinsic Motivation Inventory (IMI) subscales, change this relationship. These aspects include Interest/Enjoyment, Perceived Competence, Effort/Importance, Pressure/Tension, Perceived Choice, Value/Usefulness, and Relatedness.

IMI Subscale	ATAR Estimate	IMI Subscale Estimate	Interaction Estimate (ATAR:IMI Subscale)	p-value	RMSE
Interest/Enjoyment	0.055	0.208	-0.003	< 0.001	0.352
Perceived Competence	0.057	0.248	-0.003	< 0.001	0.247
Effort/Importance	0.054	0.358	-0.005	< 0.001	0.259
Pressure/Tension	0.055	0.413	-0.005	< 0.001	0.328
Perceived Choice	0.054	0.267	-0.003	< 0.001	0.282
Value/Usefulness	0.054	0.244	-0.003	< 0.001	0.297
Relatedness	0.056	0.265	-0.003	< 0.001	0.290

Table 5.6.4. 1:Variable Significance Impact on AT3

The analysis done from Moderator analysis conclusively shows that all IMI subscales significantly impact the relationship between ATAR scores and AT3 grades. This implies that varying motivation levels, reflecting students' perceived effort and competence, alter the correlation between their ATAR scores and AT3 grades. ATAR scores consistently serve as significant predictors of AT3 grades, irrespective of differing motivational states.

In conclusion, the IMI subscales' motivational factors play a significant role in determining the relationship between ATAR scores and academic performance, with ATAR scores persistently being a robust predictor of academic results, regardless of the motivational backdrop.

5.6.6 Logistic regression modelling

The main goal of employing logistic regression in this context is to examine how various predictors, like ATAR scores and IMI subscales, affect the binary categorization of AT3 grades, representing the students' pass or fail status.

Variable	Estimate	Std. Error	z value	p-values
Mode	-0.34050	0.48596	-0.701	0.48350
ATAR	0.04842	0.01580	3.064	0.00218
Gender	-0.81903	0.56527	-1.449	0.14736
IMI - Pressure/Tension	-0.11491	0.08028	-1.431	0.15233
AT2 article summary Wk 5	0.15973	0.10056	1.589	0.11217
IM_Percentage	-0.03399	0.02359	-1.440	0.14973
Motivation_Type	-0.49884	0.56664	-0.880	0.37867
Campus_transformed	-0.52310	0.53520	-0.977	0.32838
Age_Group	0.17763	0.50270	0.353	0.72383

Table 5.6.5. 1:Baseline logistic regression results

Using Logistic regression, The study initiated the implementation a baseline Logistic Regression model, utilizing all accessible variables in the dataset as prospective predictors. This foundational model attained an accuracy rate of approximately 75.28 %, accurately classifying this percentage of instances.

5.6.6.1 *Variable Selection for logistic model using stepwise regression*

The next step will involve identifying and incorporating only the most significant variables to enhance the model's predictive accuracy using stepwise regression. These variables will be selected based on statistical significance, predictive power, and relevance to the academic domain.

Variable	Estimate	Std. Error	z value	p-values
ATAR	0.04777	0.01366	3.497	0.000471
IMI - Pressure/Tension	-0.12884	0.07166	-1.798	0.072169
IM_Percentage	-0.03623	0.01427	-2.539	0.011127

Table 5.6.5.1. 1:Variable Importance For Logistic Regression using Stepwise

After utilizing the stepwise method for variable selection, the refined logistic regression model, incorporating ATAR, IMI - Pressure/Tension, AT2, and IM_Percentage, exhibited an accuracy of 66.66%, a decrease from the initial model's 75.28%. Given the emphasis on predictive accuracy in this study, it's pivotal to refine the stepwise-selected variable model further to meet the research objectives more effectively. The diminished accuracy underscores the necessity for meticulous variable selection and rigorous model evaluation to guarantee dependable predictions on new data.

5.6.6.2 *Variable Selection for Logistic Model using Variable Importance*

Variable	Estimate	Std. Error	z value	p-values
ATAR	0.04924	0.01589	3.099	0.00194
Age_Group	0.18198	0.50113	0.363	0.71649
Gender	-0.85649	0.55772	-1.536	0.12461
IMI - Pressure/Tension	-0.11956	0.07962	-1.502	0.13321
AT2	0.14000	0.09335	1.500	0.13366
IM_Percentage	-0.03320	0.02333	-1.423	0.15477
Motivation_Type	-0.54299	0.55977	-0.970	0.33203
Campus_transformed	-0.62551	0.51533	-1.214	0.22482

Table 5.6.5.2. 1:Logistic Regression Variables Using the Variables of Variable Importance

After applying stepwise regression, the refined Logistic Regression model reached an accuracy rate of 68.5 % using Logistic regression using variable importance variables. This does not represent an improvement over the baseline model, which had an accuracy of 75.28%. Moreover, the model refined using variable importance did not achieve a higher accuracy than the baseline model. In the variable importance approach, variables were selected based on their contribution to the model's predictive capability, as quantified through importance scores.

5.6.6.3 *Logistic Regression Interaction terms*

Variable	Estimate	Std. Error	z value	p-values
ATAR	-0.1691877	0.1028682	-1.645	0.1000
AT2	-0.1243174	0.4746902	-0.262	0.7934
IM_Percentage	0.1456666	0.1213790	1.200	0.2301
ATAR:AT2	0.0145163	0.0072852	1.993	0.0463
ATAR:IM_Percentage	-0.0001782	0.0014452	-0.123	0.9019

AT2:IM_Percentage	-0.0108165	0.0072240	-1.497	0.1343

Table 5.6.5.3. 1:Logistic Regression variables using interaction terms

In the logistic regression model, interaction terms were included using Logistic Regression using Interaction terms, and variable selection was explicitly guided by their significance in preceding models. ATAR, AT2, and IM_Percentage were integrated with interaction terms due to their significance or their intriguing role in the model.

The summary showed the interaction term between ATAR and AT2 to be statistically significant, with a p-value of 0.0463, signifying the substantial impact of the combined effect of these variables on the dependent variable. Conversely, other interaction terms like ATAR: IM_Percentage and AT2: IM_Percentage weren't statistically significant, with p-values exceeding the standard alpha level of 0.05, implying that the interaction of these variables doesn't significantly affect the outcome variable when other variables are considered in the model.

Concerning predictive accuracy, the model with interaction terms reached approximately 74.16% using Logistic Regression using Interaction terms, showing enhanced predictive capability compared to some earlier models.

In conclusion, the logistic regression model with interaction terms from significant variables offers a refined and accurate structure for predicting the dependent variable. The notable interaction between ATAR and AT2 and the improved accuracy rate of 74.16% make this model a trustworthy choice for interpreting the factors influencing the dependent variable. This improvement in accuracy emphasizes the value of considering interaction effects between predictors in the model to obtain more detailed insights.

Variable	Estimate	Std. Error	z value	Pr(>
ATAR	-0.049389	0.025568	-1.932	0.05340
AT2	-0.236295	0.073522	-3.214	0.00131
ATAR: AT2	0.006224	0.001897	3.280	0.00104

Table 5.6.5.3. 2:Logistic regression variables using significant interactions

In the refined analysis, a logistic regression model was developed, incorporating only significant variables from the interaction terms model, specifically ATAR, AT2, and their interaction term, ATAR: AT2.

Contrary to initial findings, the model summary revealed that both AT2 and the interaction term ATAR: AT2 were statistically significant, with p-values below the conventional 0.05 threshold, denoting their considerable impact on the dependent variable. However, ATAR, when considered alone, did not achieve statistical significance at this level, indicating its influence isn't statistically substantial when evaluated with other variables in the model.

In summary, while including interaction terms in the logistic regression model added complexity and nuance, it did not necessarily improve predictive accuracy. The model with only significant interaction terms had a lower accuracy rate of 67.415%, suggesting that a more complex model does not always yield better results. Therefore, the logistic regression model refined using stepwise regression remains the most robust choice for fulfilling the research objectives.

5.6.7 Support Vector Machine(SVM) for classification

5.6.7.1 *Linear Kernel*

In a recent machine learning application, a Support Vector Machine (SVM) model was developed for the classification task of predicting `AT3_Median_Performance` within a given dataset, `log_regression_data`. The SVM model, characterized by its use of a linear kernel and specified as a C-classification type, demonstrated a notable performance with an accuracy of 73.03%. This linear kernel implies an assumption of linear separability in the data, where the decision boundary between different classes can be represented as a linear function. The model was configured with a default cost parameter (`C`) of 1, balancing the trade-off between maximizing the margin and minimizing the classification error. With a total of 65 support vectors, the model encapsulates the critical data points that define the decision boundary. This accuracy metric and the model's configuration highlight its effectiveness in classifying the target variable, reflecting a substantial potential for predictive tasks in similar academic or research settings.

5.6.7.2 *Radial Bias Function*

In a sophisticated application of machine learning within an academic context, a Support Vector Machine (SVM) employing a Radial Basis Function (RBF) kernel was utilized to classify and predict `AT3_Median_Performance` from the `log_regression_data` dataset. The model underwent a detailed hyperparameter tuning process, focusing primarily on optimizing the gamma parameter—a key determinant in the performance of the RBF kernel. This process culminated in the identification of an optimal model, defined by its C-classification type and radial kernel. Notably, the model was configured with a cost parameter of 1, which serves to balance the model's complexity against its margin of error on the training data. The model incorporated 76 support vectors, indicative of the essential data points that critically influence the formation of the decision boundary. A significant highlight of this model was its achievement of an accuracy of 82.02%, showcasing its enhanced ability to discern and capture the complex, non-linear relationships inherent in the dataset. This level of accuracy not only reflects the model's robust predictive capabilities but also underscores the effectiveness of employing an SVM with an RBF kernel in sophisticated classification tasks within research and academic domains.

5.6.8 Optimal linear regression model

Model	RMSE	Adj-Rsq(%)	Difference in Multiple Rsq and Adj-Rsq
Baseline Linear Regression	0.31	99.42	0.06
Stepwise Linear Regression	0.31	99.42	0.06
Linear regression from variable selected from Tree Regression	0.37	99.23	0.05
Linear regression using interaction terms	0.20	99.76	0.02

Linear regression for Hybrid Mode including all variables	0.263	99.53	0.09
Linear regression for online Mode including all variables	0.402	99.32	0.14
Linear regression With AT2 and AT3	0.619	97.89	0.02
Linear regression for AT2 and At3 for Online Mode	0.739	96.95	0.07
Linear regression for AT2 and AT3 for Hybrid Mode	0.483	98.71	0.03
Linear regression for AT2-AT3 for all variables	0.096	45.34	5.53
Linear regression for AT2-AT3 for Mode as Hybrid	0.057	65.64	5.98
Linear regression for AT2-AT3 for Mode as Online	0.135	33.73	12.33
Decision Tree Regression	0.17	56.97	0.05
Pruned Tree Regression	0.19	70.57	0.03
SVM regression with linear kernel	0.203	-	-
SVM regression with RBF kernel	0.164	-	-

Table 5.6.8. 1:All regression model results

In conclusion, while the "Linear regression using interaction terms" model emerges as a superior predictor for "AT3," marked by an impressive RMSE of 0.20 and an outstanding Adjusted R-squared value of 99.76%, it's noteworthy to consider the performance of SVM regression with an RBF kernel. This model, particularly when focusing solely on RMSE, presents itself as a robust contender. It excels in capturing complex, non-linear relationships inherent in the data, a capability that linear models may not fully harness. The baseline and stepwise regression approaches, with commendable RMSEs and high Adjusted R-squared values, along with the tree regression-informed linear model, also demonstrate significant predictive power. The Pruned Tree Regression, with an RMSE of 0.19 and an Adjusted R-squared of 70.57%, further underscores the potential of tree-based models. However, among the linear models, the "Linear regression using interaction terms" stands out for its precision and reliability in predicting "AT 3" outcomes. This comparison highlights the importance of model selection based on the specificities of the dataset and the analytical objectives, acknowledging that different models may excel under varying criteria such as RMSE or Adjusted R-squared.

5.6.9 Optimal logistic regression model

Model	**Variables**	**Accuracy**
Baseline Logistic Regression	Mode, ATAR, Age_Group, Gender, IMI - Pressure/Tension, AT2, IM_Percentage, Motivation_Type, Campus_transformed	75.28 %
Stepwise Logistic Regression	ATAR, IMI - Pressure/Tension, AT2, IM_Percentage	69.66 %
Logistic regression using Variable Importance	ATAR, Age_Group, Gender, IMI - Pressure/Tension, AT2, IM_Percentage, Motivation_Type, Campus_transformed	68.53 %
Logistic regression using interaction terms	ATAR, AT2, IM_Percentage, ATAR:AT2, ATAR: IM_Percentage, AT2:IM_Percentage	74.157 %
Logistic regression using Significant interaction terms	ATAR, AT2, ATAR: AT2	67.416 %

Table 5.6.9. 1:Logistic regression model summary

Based on the provided data, the Baseline Logistic Regression model stands out with a commendable accuracy of 75.28%, incorporating a comprehensive range of variables. The Logistic Regression model utilizing interaction terms also demonstrates strong performance, boasting a high accuracy rate of 74.157%. On the other hand, models such as the Stepwise Logistic Regression and the Logistic Regression using Significant Interaction Terms present with slightly lower accuracies of 69.66% and 67.416%, respectively. In comparison, the Logistic regression using Variable Importance yields an accuracy of 68.53%. Consequently, for achieving the most precise predictions, both the Baseline Logistic Regression and the Logistic Regression model with interaction terms prove to be highly effective, underscoring the significance of considering an extensive set of variables and the combined effects of interactions in predictive modelling.

5.6.9.1 *Optimal SVM model*

Kernel	Accuracy
Linear	73.03
Radial Bias Function (RBF)	82.02

Table 5.6.9.1. 1:SVM Model summary

In the comparison of SVM classification models, the model with the Radial Bias Function (RBF) kernel proved to be the most effective, achieving an accuracy of 82.02%, surpassing the Linear kernel model's accuracy of 73.03%. This indicates that the RBF kernel, with its ability to handle complex, non-linear data patterns, is the superior choice for this specific classification task.

5.6.10 Data Modelling summary

Our study showed that the Linear Regression model with interaction terms was the best for regression tasks, having the lowest RMSE of 0.20 if we look at the Adjusted Rsquare as well but if we look at RMSE only SVM regression with kernel function is the optimal model. For classification, the SVM model with was the top performer with an accuracy of 82.02%. These models are the most effective for their respective tasks in this research.

6 DISCUSSION AND SUMMARY OF RESULTS

In this research, a comprehensive exploration of the dataset revealed distinct characteristics between Online and Hybrid teaching modes. While Hybrid mode students exhibited higher ATAR scores and intrinsic motivation, Online mode students showcased superior course averages and system usability scores. The meticulous data cleaning process ensured dataset reliability, with derived variables offering insights into student motivations and Hybrid mode preferences. Statistical analyses indicated no significant differences in AT3 grades based on study mode, motivation type, or gender. Data preprocessing, particularly the transformation of variables, set the stage for accurate modelling, with the “Linear regression using interaction terms” model emerging as the most effective in explaining the variance in "AT3". This study provides a general understanding of student performance in different teaching modes, emphasizing the importance of intrinsic motivation and its potential influence on academic outcomes. (OpenAI, 2023)

7 REFERENCES

Abdelrahman, N., & Irby, B. J. (2016). Hybrid Learning:Perspectives of Higher Education Faculty. *Hybrid Learning*.

Australian Tertiary Admission Rank. (2023, September 19). *Wikipedia*. Retrieved from Australian Tertiary Admission Rank: https://en.wikipedia.org/wiki/Australian_Tertiary_Admission_Rank

Firat, Kilinç, H., & Yüzer. (2018). Level of intrinsic motivation of distance education students in e-learning enviorments. *Journal of Computer Assisted Learning*, 63-70.

Goodyear, P. (2020). Design and co-configuration for hybrid learning: Theorising the practices of learning space design. *British Journal of Educational Technology*.

Gunuc, S., & Kuzu, A. (2014). Student engagement scale: development, reliability and validity. *Assessment & Evaluation in Higher Education*, 587-610.

Latrobe University. (2022). *HLT1RAE - Reflective and Evidence-Based Practice in Health Care.* Retrieved from La Trobe University Handbook.: https://handbook.latrobe.edu.au/subjects/2023/HLT1RAE?offering=Select+Offering

Latrobe University. (2023, July 1). Information regarding IMI. Melbourne, Victoria, Australia.

McEldoon, K., & Schneider, E. (2020, July). *7 Tips from Research for Effective Hybrid Teaching*. Retrieved from Pearson Education - Pedagogy Blog: https://www.pearson.com/ped-blogs/blogs/2020/07/7-tips-from-research-for-effective-hybrid-teaching.html

Montclair State University. (n.d.). *Pedagogical Strategies and Practices*. Retrieved from Montclair State University - Instructional Technology and Design Services: https://www.montclair.edu/itds/digital-pedagogy/pedagogical-strategies-and-practices/

Munaro, E. (2021, March 30). *Phygital Teaching: How a Hybrid Education Could Shape the Future*. Retrieved from Cambridge English Language Teaching Blog: https://www.cambridge.org/elt/blog/2021/03/30/phygital-teaching-how-a-hybrid-education-could-shape-the-future/

O'Byrne, W. I., & Pytash, K. E. (2015). Hybrid and Blended Learning : Modifying Pedagogy Across Path, Pace, Time, and Place. *Journal of Adolescent & Adult Literacy*.

OpenAI. (2023, November 8). *ChatGPT*. Retrieved from ChatGPT 4[Large language model]: https://chat.openai.com/

Ostrow, K. S., & Heffernan, N. T. (n.d.). Testing the Validity and Reliability of Intrinsic Motivation Inventory Subscales Within ASSISTments.

Ryan, & Deci. (2000). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*.

Ryan, & R.M. (n.d.). Control and information in the intrapersonal sphere: An extension of cognitive evaluation theory. *Journal of Personality and Social Psychology*, 450–461.

Sultana, & Awais. (2022). Proceedings of the Unima International Conference on Social Sciences and Humanities (UNICSSH 2022). *Learning Design in the Aftermath of COVID-19: Lessons from Online and Hybrid Learning During the Pandemic*.

Vallerand, J., R., Pelletier, G., L., Blais, R., M., . . . F, E. (n.d.). The Academic Motivation Scale: A Measure of Intrinsic, Extrinsic, and Amotivation in Education. *Educational and Psychological Measurement*.

Walker, C. O., Greene., B. A., & Mansell, R. A. (2005). Identification with academics, intrinsic/extrinsic motivation, and self-efficacy as predictors of cognitive engagement. *Learning and Individual Differences*, 1-12.

8 APPENDIX

8.1 APPENDIX A: COURSE/SUBJECT WEIGHTED AVERAGE

The Course Weighted Average is a method used to calculate the overall grade for a course, considering the different weights or contributions of various graded components within that course. A course typically consists of several components such as assignments, quizzes, midterm exams, final exams, participation, and projects, each having its own assigned weight. These weights are expressed as percentages and represent the importance of each component in determining the final grade, with the total of all weights equating to 100%.

To calculate the Course Weighted Average, each component's grade is multiplied by its respective weight. For instance, if assignments have a weight of 20% and a student scores 80% in them, the weighted grade for assignments would be ($80\% \times 20\% = 16\%$). This process is repeated for all the components of the course.

After obtaining the weighted grades for all components, they are summed up to get the Total Weighted Grade. For example, if the weighted grades for assignments, midterm exams, and final exams are 16%, 27%, and 35% respectively, the Total Weighted Grade would be ($16\% + 27\% + 35\% = 78\%$).

Finally, the Course Weighted Average is derived by dividing the Total Weighted Grade by the total weights, which is usually 100%. In the given example, the Course Weighted Average would be 78%. This calculated average effectively reflects the performance of a student in a course, considering the varied significance of each graded component.

8.2 APPENDIX B: AUSTRALIAN TERTIARY ADMISSION RANK (ATAR)

The Australian Tertiary Admission Rank (ATAR) is a percentile ranking between 0.00 and 99.95, used in Australia to compare the academic achievement of secondary school leavers who aspire to enrol in universities. It's calculated through a multifaceted process involving the scaling of marks to ensure comparability, the formation of an aggregate score from the scaled marks, and subsequently ranking students based on these aggregate scores to derive the ATAR. This ranking system is pivotal for universities to set course cut-offs and make admission decisions, serving as a standardized and equitable measure to compare students from various backgrounds. While it's a crucial element in the Australian education system, enabling students to understand their academic standing and set educational goals, its emphasis on academic achievement overlooks other significant factors like extracurricular activities and personal qualities, and the pursuit of a high ATAR can induce significant stress among students, prompting discussions about a more holistic approach to admissions.

8.3 Appendix C: Intrinsic motivation sub-scales:

1. **IMI - Interest/Enjoyment:** Interest/Enjoyment, highlights the essential role that curiosity and pleasure play in our lives. Interest drives us to explore and learn, while enjoyment brings satisfaction and fulfilment. Embracing IMI can lead to personal growth, enriching experiences, and a more meaningful life journey.
2. **Perceived Competence:** This aspect reflects how confident and capable we feel in a particular activity or subject. When we perceive ourselves as competent, our interest and enjoyment in that area tend to increase.
3. **Effort/Importance:** The level of effort we believe is necessary for an activity and how important we consider it impacts our motivation. If we see a task as significant and are willing to invest effort, our interest and enjoyment are likely to rise.
4. **Pressure/Tension:** The presence of external pressure or tension, such as deadlines or high expectations, can affect our interest and enjoyment negatively, as it might lead to stress and anxiety.
5. **Perceived Choice:** When we have a sense of autonomy and choice in selecting an activity, our interest and enjoyment tend to be higher. Feeling forced into something can have the opposite effect.
6. **Value/Usefulness:** If we perceive that an activity has value or usefulness, we are more likely to be interested and find enjoyment in it, as it aligns with our goals and needs.
7. **Relatedness:** The feeling of connection with others or the subject matter can influence our interest and enjoyment. Activities that foster a sense of relatedness are often more engaging.
8. **IMI Total:** The "IMI Total" refers to the cumulative sum of all seven factors: Perceived Competence, Effort/Importance, Pressure/Tension, Perceived Choice, Value/Usefulness, Relatedness, and Interest/Enjoyment. This sum provides an overall assessment of an individual's motivation and engagement in a particular activity or context.

8.4 Appendix D: System Usability Scale:

The System Usability Scale (SUS) is a tool for evaluating the usability of systems or products through a questionnaire-based approach. This questionnaire comprises ten statements, with respondents rating their agreement on a scale from 1 to 5, representing "Strongly Disagree" to "Strongly Agree." The SUS score is calculated by converting these ratings into a standardized range, yielding a final score that quantifies perceived usability.

To compute the SUS score, odd-numbered responses (1, 3, 5, 7, 9) are reduced by 1. Even-numbered responses (2, 4, 6, 8, 10) are subtracted from 5, and then 1 is subtracted from the result. The converted scores from all questions are summed up. This sum is then multiplied by 2.5, scaling the score to a 0-100 range.

The SUS score provides an overall usability assessment, offering a straightforward method for evaluation and analysis. However, while it furnishes a general measure of system usability from the user's viewpoint, it doesn't delve into specific usability concerns. On average, SUS scores typically centre around 68, but this can vary based on the context and user demographics.

8.5 Appendix E: Intrinsic and Extrinsic classification by percentage:

8.5.1 Intrinsic Motivation Questions:

- *I enjoyed the workshops very much.(5 is Higher Scale and 1 is Lower)*
- *I would describe the workshops as interesting.(5 is Higher Scale and 1 is Lower)*
- *While I was doing the workshops, I felt engaged.(5 is Higher Scale and 1 is Lower)*
- *I was very capable in the workshops.(5 is Higher Scale and 1 is Lower)*
- *After engaging with the workshops for a while, I felt fairly competent.(5 is Higher Scale and 1 is Lower)*
- *I was satisfied with my performance in the workshops.(5 is Higher Scale and 1 is Lower)*
- *I put a lot of effort into the workshops.(5 is Higher Scale and 1 is Lower)*
- *I tried very hard in the workshops.(5 is Higher Scale and 1 is Lower)*
- *R) I did not feel nervous at all while doing the workshops.(5 is Higher Scale and 1 is Lower)*
- *R) I was very relaxed in the workshops.(5 is Higher Scale and 1 is Lower)*
- *I believe I had some choice about doing the workshops.(5 is Higher Scale and 1 is Lower)*
- *I did the workshops because I wanted to.(5 is Higher Scale and 1 is Lower)*
- *I believe the workshops were of some value to me.(5 is Higher Scale and 1 is Lower)*
- *Looking back I'm glad I attended the workshops.(5 is Higher Scale and 1 is Lower)*
- *I believe doing the workshops was beneficial to me.(5 is Higher Scale and 1 is Lower)*
- *I think the workshops were important.(5 is Higher Scale and 1 is Lower)*

8.5.2 Extrinsic Motivation Questions:

- *R) I thought the workshops were boring.(1 is Higher Scale and 5 is Lower)*
- *R) The workshops did not hold my attention at all.(1 is Higher Scale and 5 is Lower)*
- *R) The workshops were something I couldn't do very well.(1 is Higher Scale and 5 is Lower)*
- *R) I didn't put much energy into the workshops.(1 is Higher Scale and 5 is Lower)*
- *I was anxious while working in the workshops.(1 is Higher Scale and 5 is Lower)*
- *I felt pressured while doing the workshops.(1 is Higher Scale and 5 is Lower)*
- *R) I only came to the workshops because I felt obliged.(1 is Higher Scale and 5 is Lower)*
- *R) I felt I had to come to the workshops or I would fall behind.(1 is Higher Scale and 5 is Lower)*

8.6 Appendix F: Survey questions from existing IMI studies:

The survey questions related to the Intrinsic Motivation Inventory (IMI) assess participants' engagement, satisfaction, and intrinsic motivation in a specific activity or learning context. These questions explore dimensions such as interest/enjoyment, perceived competence, effort/importance, pressure/tension, perceived choice, value/usefulness, and relatedness. They provide insights into participants' subjective experiences, motivations, and perceptions, helping researchers understand factors influencing engagement and developing effective teaching strategies. Following are the survey questions conducted in

I. **" Testing the Validity and Reliability of Intrinsic Motivation Inventory Subscales Within ASSISTments "**
   - → This assignment was fun to do.
   - → I enjoyed doing this assignment very much.
   - → I thought this assignment was quite enjoyable.
   - → I would describe this assignment as very interesting.
   - → While I was doing this assignment, I was thinking about how much I enjoyed it.
   - → I am satisfied with my performance on this assignment.
   - → I was pretty skilled at this assignment.
   - → I think I am pretty good at this assignment.
   - → After working on this assignment for a while, I felt pretty competent.
   - → I think I did pretty well at this assignment, compared to other students.
   - → I did this assignment because I had no choice. (R)
   - → I didn't really have a choice about doing this assignment. (R)
   - → I did this assignment because I had to. (R)
   - → I felt like I had to do this assignment. (R)
   - → I felt like it was not my own choice to do this assignment. (R)
   - → I believe I had some choice about doing this assignment.
   - → I'd really prefer not to interact with my classmates in the future. (R)
   - → I feel really distant to my classmates. (R)
   - → It is likely that my classmates and I could become friends if we interacted a lot.

II. **"Level of intrinsic motivation of distance education students in e-learning environments"**
   - → I enjoy studying in e-learning environments.
   - → I look forward to studying in e-learning environments.
   - → I'm satisfied with my studies in e-learning environments.
   - → I prefer to study in e-learning environments even if I have printed materials.
   - → I set my own learning needs.

III. **"Identification with academics, intrinsic/extrinsic motivation, and self-efficacy as predictors of cognitive engagement"**
   - → I enjoy studying in e-learning environments.
   - → I look forward to studying in e-learning environments.
   - → I'm satisfied with my studies in e-learning environments.

- → I prefer to study in e-learning environments even if I have printed materials.
- → I set my own learning needs.
- → I am certain I can learn the ideas and skills taught in the class.
- → School is important in my life.
- → For the pleasure I experience when I read interesting authors.
- → In order to obtain a more prestigious job later.
- → Honestly, I don’t know, I really feel I am wasting my time in school.
- → When I study, I take note of the material I have or have not mastered.
- → I try to memorize exactly what my instructors say in class.

IV. "Student Engagement Scale: Development, Reliability and Validity"

- → Do you believe university is beneficial for you?
- → Is university of great importance in your life?
- → Do you think the rules at university are fair for everybody?
- → Do you try not to damage anything that belongs to the university?
- → Do you give importance to university education and take it seriously?
- → Do you feel yourself as a part of the campus?
- → Do you find the campus an entertaining place?
- → Do you enjoy the activities carried out on campus?
- → Do you feel happy on campus?
- → Do you like spending time on campus?
- → Do you have close friends on campus?
- → Do you feel secure on campus?
- → Are your friends on campus always near you when you need them?
- → Do you like communicating with other students on campus?
- → Does the campus staff help you when you need them?
- → Do you take part in campus activities (sports activities, cultural activities, club activities and so on)?
- → Do you go to campus willingly?
- → Do you benefit from the facilities on campus (canteen, library, sports arenas and so on)?
- → Do you follow campus rules?
- → Do you look forward to going to campus?
- → Do you motivate yourself to learn?
- → Do you determine your own learning goals?
- → Do you try to do your best during classes?
- → Besides doing your lessons, do you further study for your lessons?
- → Is what you learn in class important for you?
- → Do you discuss what you have learned in class with your friends out of class?
- → Do you attend classes by getting prepared in advance?
- → Do you try to do your homework in the best way?

- → Do you enjoy intellectual difficulties you encounter while learning?
- → Do you spend enough time and make enough effort to learn?
- → Do you have close friend(s) in your class?
- → Are your teachers always near you when you need them?
- → Do you give importance to studying together with your classmates (in a group)?
- → Do your teachers respect you as an individual?
- → Do you like your teachers?
- → Do your classmates respect your thoughts/views?
- → Do you think your teachers are competent in their fields?
- → Do you think your courses are beneficial for you?
- → Do you respect your classmates?
- → Do you have teachers that you can share your problems with?
- → Are your classes entertaining?
- → Do you respect your teachers?
- → Are you interested in your courses?
- → Do your teachers show regard to your interests and needs?
- → Do you like doing something for your classmates?
- → Do you feel yourself as a part/member of a student group?
- → Do you like communicating with your teachers?
- → Do you feel anxious when you don't attend classes?
- → Do you like seeing your friends in class?
- → Are you an active student in class?
- → Do your teachers behave fairly to all your friends?
- → Do you attend classes willingly?
- → Do you carefully listen to your teacher in class?
- → Do your teachers interact/communicate with you?
- → Do you follow the rules in class?
- → Do you do your homework/tasks in time?
- → Do you carefully listen to other students in class?
- → I try to do my best regarding my responsibilities in group work
- → I share information with my classmates

V. "Latrobe University"

- → I enjoyed the workshops very much.
- → I thought the workshops were boring (R).
- → The workshops did not hold my attention at all (R).
- → I would describe the workshops as interesting.
- → While I was doing the workshops, I felt engaged.

- → I was very capable in the workshops.
- → After engaging with the workshops for a while, I felt fairly competent.
- → I was satisfied with my performance in the workshops.
- → The workshops were something I couldn't do very well (R).
- → I put a lot of effort into the workshops.
- → I tried very hard in the workshops.
- → I didn't put much energy into the workshops (R).
- → I did not feel nervous at all while doing the workshops (R).
- → I was very relaxed in the workshops (R).
- → I was anxious while working in the workshops.
- → I felt pressured while doing the workshops.
- → I believe I had some choice about doing the workshops.
- → I only came to the workshops because I felt obliged (R).
- → I felt I had to come to the workshops or I would fall behind (R).
- → I did the workshops because I wanted to.
- → I believe the workshops were of some value to me.
- → Looking back, I'm glad I attended the workshops.
- → I believe doing the workshops was beneficial to me.
- → I think the workshops were important.
- → I felt really distant to others during the workshops (R).
- → I'd like a chance to interact with others in the workshops more often.
- → I'd really prefer not to interact with others in the workshops in the future (R).
- → It is likely that others in the workshops and I could become friends if we interacted more.

The survey questions from Latrobe University's IMI focus on measuring intrinsic motivation within the context of workshops. These questions explore interest/enjoyment, perceived competence, effort/importance, value/usefulness, relatedness, and perceived choice specifically related to workshop experiences.

In contrast, the questions used in the referenced studies cover a broader range of motivational factors and academic engagement. While the exact questions may vary, the studies encompass dimensions such as self-efficacy, cognitive and behavioural engagement, identification with academics, relationships with faculty and peers, and overall academic engagement. (Firat, Kilinç, & Yüzer, 2018)

To summarize, the survey questions from Latrobe University's IMI specifically target intrinsic motivation within workshops. In contrast, the questions used in the referenced studies explore a more comprehensive range of motivational factors and academic engagement in various educational settings.

8.7 APPENDIX G: R CODES

8.7.1 Box-cox transformation

```
BCTransform <- function(y, lambda=0) {
  if (lambda == 0L) { log(y) }
  else { (y^lambda - 1) / lambda }
  }
regression_data$`AT3`<-BCTransform(regression_data$`AT3`,0)
```

8.7.2 Code to calculate RMSE for Regression

```
# Function to calculate RMSE for a linear regression model
calculate_RMSE <- function(model, data, target_column) {
 # Step 1: Predict values using the model
 predicted_values <- predict(model, newdata = data)
 # Step 2: Calculate the residuals
 residuals <- data[[target_column]] - predicted_values
 # Step 3: Square the residuals
 squared_residuals <- residuals^2
 # Step 4: Take the mean of squared residuals
 mean_squared_residuals <- mean(squared_residuals)
 # Step 5: Take the square root
 RMSE <- sqrt(mean_squared_residuals)
 # Print RMSE
 print(paste("Root Mean Square Error (RMSE): ", RMSE))
}
```

8.7.3 Baseline linear regression model

```
# Perform linear regression
model <- lm(`AT3` ~ .-1,data = lin_regression_data)
# Print the model summary
summary(model)
# Generate diagnostic plots
par(mfrow=c(2,2))  # Arrange plots in a 2x2 grid
plot(model)
```

Output:

```
Call:
lm(formula = `AT 3: Critical appraisal essay Wk9` ~ . - 1, data = lin_regression_data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.65260 -0.25995 -0.00987  0.27603  0.86745 

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)    
Mode                       0.174844   0.071100   2.459  0.01609 *  
ATAR                       0.011756   0.001957   6.007 5.30e-08 ***
Age                        0.005714   0.005174   1.104  0.27281    
Gender                     0.288008   0.081664   3.527  0.00070 ***
`IMI - Pressure/Tension`   0.036654   0.011680   3.138  0.00238 ** 
`AT2 article summary Wk 5?` 0.084859   0.013104   6.476 7.08e-09 ***
IM_Percentage              0.007193   0.003308   2.174  0.03263 *  
Motivation_Type            0.203528   0.081853   2.486  0.01498 *  
Campus_transformed         0.099198   0.052414   1.893  0.06203 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3377 on 80 degrees of freedom
Multiple R-squared:  0.9944,	Adjusted R-squared:  0.9938 
F-statistic:  1588 on 9 and 80 DF,  p-value: < 2.2e-16
```

Figure 1: Baseline Linear Regression Model

8.7.4 Stepwise linear regression model

Load necessary library

library(stats)

Perform stepwise regression

stepwise_model <- step(model, direction = "both")

Summary of the selected model

summary(stepwise_model)

Generate diagnostic plots

par(mfrow=c(2,2)) # Arrange plots in a 2x2 grid

plot(stepwise_model)

Output

```
Call:
lm(formula = `AT 3: Critical appraisal essay Wk9` ~ Mode + ATAR +
    Gender + `IMI - Pressure/Tension` + `AT2 article summary Wk 5?` +
    IM_Percentage + Motivation_Type + Campus_binary - 1, data = lin_regression_data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.67271 -0.22991  0.00147  0.27435  0.87902

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
Mode                        0.170635   0.071094   2.400 0.018683 *
ATAR                        0.011953   0.001952   6.124 3.11e-08 ***
Gender                      0.282773   0.081637   3.464 0.000854 ***
`IMI - Pressure/Tension`    0.036705   0.011696   3.138 0.002371 **
`AT2 article summary Wk 5?` 0.088126   0.012783   6.894 1.08e-09 ***
IM_Percentage               0.007924   0.003245   2.442 0.016803 *
Motivation_Type             0.205085   0.081952   2.503 0.014343 *
Campus_binary               0.110701   0.051437   2.152 0.034362 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3382 on 81 degrees of freedom
Multiple R-squared:  0.9943,    Adjusted R-squared:  0.9938
F-statistic:  1782 on 8 and 81 DF,  p-value: < 2.2e-16
```

Figure 2:Stepwise Linear Regression

8.7.5 Linear regression with variables selected From Regression Tree using variable importance

#Select impotrant variables for linear regression

variable_importance <- tree_model$variable.importance

print(variable_importance)

Perform linear regression

Train linear regression model with important variables fron Decison tree Regression

best_lin_model <- lm(`AT3` ~ (ATAR +IM_Percentage+Age_group+`AT2`+`IMI - Pressure/Tension`+Campus_transformed+Mode)-1,data = lin_regression_data)

Print the model summary

summary(best_lin_model)

Generate diagnostic plots

par(mfrow=c(2,2)) # Arrange plots in a 2x2 grid

plot(best_lin_model)

Output

```
Call:
lm(formula = `AT 3: Critical appraisal essay Wk9` ~ (ATAR + IM_Percentage +
    Age + `AT2 article summary Wk 5?` + `IMI - Pressure/Tension` +
    Campus_binary + Mode) - 1, data = lin_regression_data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.84978 -0.22120 -0.00994  0.25362  0.78644

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
ATAR                        0.013394   0.002083   6.430 7.99e-09 ***
IM_Percentage               0.014057   0.003030   4.639 1.31e-05 ***
Age                         0.004912   0.005616   0.875 0.384359
`AT2 article summary Wk 5?` 0.086165   0.014245   6.049 4.16e-08 ***
`IMI - Pressure/Tension`    0.044428   0.012518   3.549 0.000643 ***
Campus_binary               0.072619   0.056520   1.285 0.202468
Mode                        0.228744   0.075929   3.013 0.003444 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3673 on 82 degrees of freedom
Multiple R-squared:  0.9933,    Adjusted R-squared:  0.9927
F-statistic:  1724 on 7 and 82 DF,  p-value: < 2.2e-16
```

Figure 3:Linear regression with variables selected From Regression Tree using variable importance

8.7.6 Linear regression with interaction terms

Fit the model with interaction terms

linear_interaction_model <- lm(`AT3` ~((Mode + ATAR +Gender+`AT2` +IM_Percentage + Motivation_Type + Campus_transformed)^2)-1, data = lin_regression_data)

Summary of the model

summary(linear_interaction_model)

Generate diagnostic plots

par(mfrow=c(2,2)) # Arrange plots in a 2x2 grid

plot(linear_interaction_model)

Output

```
Call:
lm(formula = `AT 3: Critical appraisal essay Wk9` ~ ((Mode +
    ATAR + Gender + `AT2 article summary Wk 5?` + IM_Percentage +
    Motivation_Type + Campus_transformed)^2) - 1, data = lin_regression_data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.49912 -0.06515 -0.00030  0.08265  0.41524

Coefficients:
                                                Estimate Std. Error t value Pr(>|t|)
Mode                                           1.036e+00  5.981e-01   1.731  0.08843 .
ATAR                                           4.370e-02  1.292e-02   3.382  0.00126 **
Gender                                         2.217e-01  5.071e-01   0.437  0.66356
`AT2 article summary Wk 5?`                    1.032e-01  8.061e-02   1.281  0.20513
IM_Percentage                                  1.450e-02  2.067e-02   0.701  0.48571
Motivation_Type                               -3.676e-01  6.884e-01  -0.534  0.59531
Campus_transformed                             9.349e-01  4.881e-01   1.915  0.06014 .
Mode:ATAR                                     -3.857e-03  3.005e-03  -1.284  0.20410
Mode:Gender                                   -1.658e-01  1.227e-01  -1.352  0.18150
Mode:`AT2 article summary Wk 5?`              -8.141e-03  2.383e-02  -0.342  0.73378
Mode:IM_Percentage                             4.873e-03  4.720e-03   1.032  0.30596
Mode:Motivation_Type                          -2.946e-01  1.030e-01  -2.860  0.00579 **
Mode:Campus_transformed                       -2.005e-01  8.338e-02  -2.404  0.01926 *
ATAR:Gender                                   -3.429e-03  3.288e-03  -1.043  0.30110
ATAR:`AT2 article summary Wk 5?`              -1.186e-03  7.369e-04  -1.610  0.11262
ATAR:IM_Percentage                             5.039e-05  1.280e-04   0.394  0.69522
ATAR:Motivation_Type                          -2.708e-03  3.724e-03  -0.727  0.46993
ATAR:Campus_transformed                       -5.856e-03  2.578e-03  -2.271  0.02668 *
Gender:`AT2 article summary Wk 5?`             3.129e-02  2.207e-02   1.418  0.16138
Gender:IM_Percentage                          -3.830e-03  5.659e-03  -0.677  0.50112
Gender:Motivation_Type                         1.652e-02  1.241e-01   0.133  0.89459
Gender:Campus_transformed                      3.703e-02  1.684e-01   0.220  0.82670
`AT2 article summary Wk 5?`:IM_Percentage     -2.038e-03  8.489e-04  -2.401  0.01941 *
`AT2 article summary Wk 5?`:Motivation_Type    4.598e-02  2.902e-02   1.585  0.11822
`AT2 article summary Wk 5?`:Campus_transformed 1.315e-02  2.281e-02   0.577  0.56630
IM_Percentage:Motivation_Type                  6.496e-03  5.340e-03   1.216  0.22849
IM_Percentage:Campus_transformed              -4.454e-03  3.933e-03  -1.132  0.26195
Motivation_Type:Campus_transformed            -5.455e-02  8.761e-02  -0.623  0.53586
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1854 on 61 degrees of freedom
Multiple R-squared:  0.9987,    Adjusted R-squared:  0.9981
F-statistic:  1701 on 28 and 61 DF,  p-value: < 2.2e-16
```

Figure 4:Linear regression with variables selected From Regression Tree using interaction terms

8.7.7 Linear regression using significant interaction terms

Create the linear regression model with significant interaction terms

linear_significant_interaction <- lm(`AT3` ~ (ATAR+Mode:Motivation_Type+Mode:Campus_transformed+ATAR:Campus_transformed+`AT2`:IM_Percentage)-1, data = lin_regression_data)

Summary of the final model

summary(linear_significant_interaction)

Generate diagnostic plots

par(mfrow=c(2,2)) # Arrange plots in a 2x2 grid

plot(linear_significant_interaction)

Output

```
Call:
lm(formula = `AT 3: Critical appraisal essay Wk9` ~ (ATAR + Mode:Motivation_Type +
    Mode:Campus_transformed + ATAR:Campus_transformed + `AT2 article summary Wk 5?
`:IM_Percentage) -
    1, data = lin_regression_data)

Residuals:
     Min       1Q   Median       3Q      Max
-1.13994 -0.30824  0.05802  0.39223  1.36020

Coefficients:
                                            Estimate Std. Error t value Pr(>|t|)
ATAR                                       0.0365269  0.0036203  10.090 3.85e-16 ***
Mode:Motivation_Type                      -0.0296994  0.0728933  -0.407 0.684724
Mode:Campus_transformed                    0.3562089  0.0879193   4.052 0.000113 ***
ATAR:Campus_transformed                   -0.0072215  0.0022365  -3.229 0.001773 **
`AT2 article summary Wk 5?`:IM_Percentage  0.0014340  0.0001787   8.024 5.44e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5451 on 84 degrees of freedom
Multiple R-squared:  0.9848,    Adjusted R-squared:  0.9839
F-statistic:  1086 on 5 and 84 DF,  p-value: < 2.2e-16
```

Figure 5:Linear regression with variables selected From Regression Tree using significant interaction terms

8.7.8 Linear regression using significant interaction by elimination of insignificant interaction

Create the linear regression model with significant interaction terms by removing one insignificant

linear_significant_interaction_insig <- lm(`AT3` ~ (ATAR+Mode:Campus_transformed+ATAR:Campus_transformed+`AT2`:IM_Percentage)-1, data = lin_regression_data)

Summary of the final model

summary(linear_significant_interaction_insig)

Generate diagnostic plots

par(mfrow=c(2,2)) # Arrange plots in a 2x2 grid

plot(linear_significant_interaction_insig)

Output

```
Call:
lm(formula = `AT 3: Critical appraisal essay Wk9` ~ (ATAR + Mode:Campus_transformed +
    ATAR:Campus_transformed + `AT2 article summary Wk 5?`:IM_Percentage) -
    1, data = lin_regression_data)

Residuals:
     Min       1Q   Median       3Q      Max
-1.16171 -0.30096  0.03126  0.38996  1.37682

Coefficients:
                                            Estimate Std. Error t value Pr(>|t|)
ATAR                                       0.0357504  0.0030629  11.672  < 2e-16 ***
Mode:Campus_transformed                    0.3294240  0.0580913   5.671 1.91e-07 ***
ATAR:Campus_transformed                   -0.0066593  0.0017514  -3.802 0.000269 ***
`AT2 article summary Wk 5?`:IM_Percentage  0.0014184  0.0001737   8.167 2.62e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5425 on 85 degrees of freedom
Multiple R-squared:  0.9847,    Adjusted R-squared:  0.984
F-statistic:  1371 on 4 and 85 DF,  p-value: < 2.2e-16
```

Figure 6:Linear regression with variables selected From Regression Tree using significant interaction terms by eliminating insignificant interactions

8.7.9 Decision tree regression

library(rpart)

library(rpart.plot)

Build the regression tree

tree_model <- rpart(`AT3` ~ .,

data = lin_regression_data,

method = "anova")

rpart.plot(tree_model)

printcp(tree_model)

Calculate and print adjusted R-squared

low_cp<-tree_model$cptable[which.min(tree_model$cptable[,"xerror"]),"CP"]

8.7.10 SVM regression with linear kernel

model_svm_linear <- svm(`AT 3: Critical appraisal essay Wk9` ~ .,data = lin_regression_data, type = "eps-regression", kernel = "linear")

predictions <- predict(model_svm_linear, newdata =lin_regression_data)

summary(model_svm_linear)

Assuming you have already fitted the SVM model and made predictions

Calculate residuals

residuals <- predictions - lin_regression_data$`AT 3: Critical appraisal essay Wk9`

Calculate MSE

mse <- mean(residuals^2)

Calculate RMSE

```
rmse <- sqrt(mse)

print(rmse)
```

8.7.11 SVM regression with RBF kernel

```
# automated tuning of gamma paramter for RBF kernel

tuned_model <- tune.svm(`AT 3: Critical appraisal essay Wk9` ~ .,data = lin_regression_data, type = "eps-regression", kernel = "radial", gamma = 10^(-3:2))

best_model <- tuned_model$best.model

predictions <- predict(best_model, newdata =lin_regression_data)

# Calculate residuals of svm

residuals <- predictions - lin_regression_data$`AT 3: Critical appraisal essay Wk9`

# Calculate MSE

mse <- mean(residuals^2)

# Calculate RMSE

rmse <- sqrt(mse)

print(rmse)
```

8.7.12 Moderator analysis

```
# List of IMI subscales

imi_subscales <- c("IMI - Interest/Enjoyment","IMI - Perceived Competence","IMI - Effort/Importance","IMI - Pressure/Tension","IMI - Perceived Choice","IMI - Value/Usefulness","IMI - Relatedness")

# Loop through each IMI subscale and run the moderator analysis

for(subscale in imi_subscales) {

 formula_str <- paste("`AT3` ~ ATAR * `", subscale, "`","-1", sep = "")

 fit <- lm(formula_str, data = regression_data)  # Note the data argument here

 # Call the calculate_RMSE function for each fit

 print(paste("Moderator Analysis for", subscale))

 print(summary(fit))

 calculate_RMSE(fit, regression_data, "AT3")

}
```

8.7.13 Logistic regression

```
library(caret)

log_regression_data<-dplyr::select(regression_data,-c(Campus,`Region origin`,`AT3`,AT3_Performance,TOTAL,TOTAL_Performance,SUS,`IMI - Interest/Enjoyment`,`IMI - Perceived Competence`,`IMI - Effort/Importance`,`IMI - Perceived Choice`,`IMI - Value/Usefulness`,`IMI - Relatedness`,`IMI Total`,EM_Percentage,Like_Hybrid,id,`Course Weighted Average`,Region_binary))

model_log <- glm(AT3_Median_Performance ~.-1,data = log_regression_data)

# Print the model summary

summary(model_log)
```

Load necessary libraries

Assuming you have a logistic regression model named 'model_log'

Assuming 'regression_data' is your dataframe with the test data

Make predictions using the logistic regression model

predictions <- predict(model_log, newdata = log_regression_data, type = "response")

Convert probabilities to class predictions

predicted_classes <- ifelse(predictions > 0.5, 1,0)

Create a data frame with actual and predicted class labels

confusion_data <- data.frame(Actual = regression_data$AT3_Median_Performance,

Predicted = predicted_classes)

print(paste("Accuracy of Basic Logistic Model is",(sum(confusion_data$Actual==confusion_data$Predicted)/nrow(confusion_data))*100))

Output

```
Call:
glm(formula = AT3_Median_Performance ~ . - 1, data = log_regression_data)

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)
Mode                         -0.084665   0.097298  -0.870 0.386816
ATAR                          0.010435   0.002678   3.896 0.000202 ***
Age                          -0.007703   0.007081  -1.088 0.279921
Gender                       -0.099033   0.111754  -0.886 0.378182
`IMI - Pressure/Tension`     -0.021371   0.015984  -1.337 0.185012
`AT2 article summary Wk 5?`   0.042737   0.017933   2.383 0.019533 *
IM_Percentage                -0.004628   0.004527  -1.022 0.309714
Motivation_Type              -0.066878   0.112013  -0.597 0.552153
Campus_binary                 0.039568   0.071726   0.552 0.582725
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.2135868)

    Null deviance: 45.000  on 89  degrees of freedom
Residual deviance: 17.087  on 80  degrees of freedom
AIC: 125.69

Number of Fisher Scoring iterations: 2
```

```
[1] "Accuracy of Basic Logistic Model is 73.0337078651685"
```

Figure 7:Basline Logistic Regression Accuracy

8.7.14 Varible selection for stepwise Logistic regression

Load necessary library

library(stats)

Perform stepwise regression

stepwise_log_model <- step(model_log, direction = "both")

Summary of the selected model

summary(stepwise_log_model)

Output

```
Call:
glm(formula = AT3_Median_Performance ~ ATAR + `IMI - Pressure/Tension` +
    `AT2 article summary Wk 5?` + IM_Percentage - 1, data = log_regression_data)

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
ATAR                       0.009563   0.002582   3.703 0.000378 ***
`IMI - Pressure/Tension`  -0.025003   0.015003  -1.667 0.099280 .
`AT2 article summary Wk 5?` 0.035150   0.016793   2.093 0.039322 *
IM_Percentage             -0.008352   0.003623  -2.305 0.023612 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.2091076)

    Null deviance: 45.000  on 89  degrees of freedom
Residual deviance: 17.774  on 85  degrees of freedom
AIC: 119.2

Number of Fisher Scoring iterations: 2
```

```
[1] "Accuracy of Stepwise Logistic Model is 66.2921348314607"
```

Figure 8:Accuracy of refined logistic regression model

8.7.15 Variable selection for Logistic regression using variable importance

Load necessary library

library(caret)

Assuming you have a logistic regression model named 'model_log'

Assess variable importance using varImp

variable_importance_log <- varImp(model_log)

print(variable_importance_log)

Output

Description: df [8 × 1]

	Overall <dbl>
ATAR	3.8961732
Age	1.0878659
Gender	0.8861707
`IMI - Pressure/Tension`	1.3369997
`AT2 article summary Wk 5?`	2.3832042
IM_Percentage	1.0223136
Motivation_Type	0.5970605
Campus_transformed	0.5516514

8 rows

Figure 9: Important variables using variable importance

8.7.16 Logistic regression using variable importance variables

Train logistic regression model with important variables

model_log <- glm(`AT3_Median_Performance` ~ (`ATAR` + `Course Weighted Average` +Age_group+Gender+`AT2` +IM_Percentage+Region_binary+Mode)-1,data = log_regression_data)

Print the model summary

summary(model_log)

Output

```
Call:
glm(formula = AT3_Median_Performance ~ (ATAR + Age + Gender +
    `IMI - Pressure/Tension` + `AT2 article summary Wk 5?` +
    IM_Percentage + Motivation_Type + Campus_transformed) - 1,
    data = log_regression_data)

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
ATAR                         0.010440   0.002674   3.904 0.000195 ***
Age                         -0.007373   0.007060  -1.044 0.299462
Gender                      -0.112113   0.110572  -1.014 0.313632
`IMI - Pressure/Tension`    -0.022518   0.015906  -1.416 0.160696
`AT2 article summary Wk 5?`  0.039785   0.017582   2.263 0.026326 *
IM_Percentage               -0.004745   0.004518  -1.050 0.296774
Motivation_Type             -0.081131   0.110642  -0.733 0.465507
Campus_transformed           0.020786   0.068298   0.304 0.761653
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.2129465)

    Null deviance: 45.000  on 89  degrees of freedom
Residual deviance: 17.249  on 81  degrees of freedom
AIC: 124.53

Number of Fisher Scoring iterations: 2
```

```
[1] "Accuracy of Logistic Model with Important Variables is 69.6629213483146"
```

Figure 10:Accuracy of logistic regression model using variable importance

8.7.17 Logistic Regression using Interaction terms

interaction_model <- glm(AT3_Median_Performance ~ (ATAR + `AT2` + IM_Percentage + ATAR:`AT2` + ATAR:IM_Percentage + `AT2`:IM_Percentage)-1, data = log_regression_data, family = binomial)

Summary of the model

summary(interaction_model)

Output

```
Call:
glm(formula = AT3_Median_Performance ~ (ATAR + `AT2 article summary Wk 5?` +
    IM_Percentage + ATAR:`AT2 article summary Wk 5?` + ATAR:IM_Percentage +
    `AT2 article summary Wk 5?`:IM_Percentage) - 1, family = binomial,
    data = log_regression_data)

Coefficients:
                                         Estimate Std. Error z value Pr(>|z|)
ATAR                                   -0.1691877  0.1028682  -1.645   0.1000
`AT2 article summary Wk 5?`            -0.1243174  0.4746902  -0.262   0.7934
IM_Percentage                           0.1456666  0.1213790   1.200   0.2301
ATAR:`AT2 article summary Wk 5?`        0.0145163  0.0072852   1.993   0.0463 *
ATAR:IM_Percentage                     -0.0001782  0.0014452  -0.123   0.9019
`AT2 article summary Wk 5?`:IM_Percentage -0.0108165  0.0072240  -1.497   0.1343
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 123.38  on 89  degrees of freedom
Residual deviance: 100.35  on 83  degrees of freedom
AIC: 112.35

Number of Fisher Scoring iterations: 4
```

```
[1] "Accuracy of Logistic Regression using interactions 74.1573033707865"
```

Figure 11:Accuracy of logistic regression model using interaction terms

8.7.18 Logistic regression with significant interactions

Logistic Regression with Only Significant Interaction Term

significant_logistic_interactions <- glm(AT3_Median_Performance ~ ATAR + `AT2` + ATAR:`AT2`, data = log_regression_data, family = binomial)

Summary of the model

summary(significant_logistic_interactions)

Output

```
Call:
glm(formula = AT3_Median_Performance ~ (ATAR + `AT2 article summary Wk 5?` +
    ATAR:`AT2 article summary Wk 5?`) - 1, family = binomial,
    data = log_regression_data)

Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)
ATAR                             -0.049389   0.025568  -1.932  0.05340 .
`AT2 article summary Wk 5?`      -0.236295   0.073522  -3.214  0.00131 **
ATAR:`AT2 article summary Wk 5?`  0.006224   0.001897   3.280  0.00104 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 123.38  on 89  degrees of freedom
Residual deviance: 105.33  on 86  degrees of freedom
AIC: 111.33

Number of Fisher Scoring iterations: 3
```

```
[1] "Accuracy of Logistic Regression using significant interactions 67.4157303370787"
```

Figure 12:Accuracy of Logistic Regression using Significant Interactions

8.7.19 SVM classification with linear kernel

model_svm_class <- svm(AT3_Median_Performance ~.,data = log_regression_data,type = "C-classification",kernel = "linear")

predictions <- predict(model_svm_class, newdata =log_regression_data)

Evaluate the model

Calculate accuracy

accuracy <- sum(predictions == log_regression_data$AT3_Median_Performance) / length(predictions)

print(accuracy*100)

8.7.20 SVM classification with RBF kernel

automated tuning of gamma paramter for RBF kernel

log_regression_data$AT3_Median_Performance <- as.factor(log_regression_data$AT3_Median_Performance)

tuned_model <- tune.svm(AT3_Median_Performance ~.,data = log_regression_data,type = "C-classification", kernel = "radial", gamma = 10^(-3:2))

best_model <- tuned_model$best.model

predictions <- predict(best_model, newdata =log_regression_data)

Evaluate the model

Calculate accuracy

accuracy <- sum(predictions == log_regression_data$AT3_Median_Performance) / length(predictions)

print(accuracy*100)

9 Code References

- *Impacts_of_hybrid_teaching_on_students_with_different_motivations_R_Script*
- *deciphering-the-impact-of-hybrid-teaching-on-student-motivation_Python_file*