The following paper was researched and written as part of LSE GROUPS 2023.

LSE GROUPS takes place during the final fortnight of the LSE summer term. Undergraduate students are placed in small groups; these are cross-year, interdisciplinary, and group members do not know one another in advance. Each group must then devise its own research question, and carry out every stage of a small-scale research project in less than two weeks.

LSE GROUPS is part of the LSE commitment to students learning through enquiry, and developing the skills for knowledge creation.

The overall theme of LSE GROUPS 2023 was *Connections.*

This paper was submitted on the final Thursday afternoon of the project.

Students then presented their work at a conference, on the closing Friday.

More information on LSE GROUPS, and other papers.

Papers are presented as submitted by the students, without corrections.

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Beyond code: Unpacking the impact of Generative AI on student interpersonal dynamics in Higher Education

LSE GROUP 6

Abstract:

Despite the mix of alarm and enthusiasm about Artificial Intelligence (AI) as an emerging field, we know little about to what extent the different usages of generative AI (e.g. Chat GPT) affect interpersonal relationships. This article seeks to address this gap in the literature on generative AI by providing new insights into students' relationships in higher education. Drawing upon the results of more than 100 survey responses from LSE students, we examine the associations between generative AI usage (measured in two dimensions as frequency and purpose of use), students' perceptions towards using it, and their sense of connection to their peers and instructors in higher education. In doing so, we aim to recentre students in higher education discourse, where they have become neglected in favour of the institutional perspective.

The paper finds that the frequency and purpose of generative AI usage do not affect students' relationships with peers or instructors. It also sheds light on how students' perceptions of generative AI affect these relationships independent of actual usage.

Despite some limitations, this study provides a framework for further, more extensive research and indicates critical directions for developing extended analysis and policy.

Keywords: Generative AI, Chat GPT, Interpersonal Relationships, Higher Education, ECR-RS, Expectancy Value Theory (EVT)

1. Introduction

Though generative AI (GenAI) has existed for quite some time now, it has only recently entered the mainstream. In January 2023, just two months after its launch, ChatGPT, the most famous and popular generative AI tool, reached 100 million monthly active users, making it the fastest-growing consumer application in history (Hu, 2023). Given the potentially disruptive nature of this technology and the opportunities and benefits it can yield, much recent academic study has been preoccupied with its emerging uses and impacts on a wide range of fields, from medicine and engineering to higher education.

In this paper, we have chosen to focus on the impact of GenAI on higher education due to the particular significance of this sector and the observation that the existing literature in the area has maintained too narrow a focus, primarily due to the lack of student voices (Sullivan et al., 2023). In the UK, there are 2 million students in higher education, with over 600,000 international students (Atherton et al., 2023). About 550,000 staff are employed in the sector, helping to train the future labour force, e.g. 191,000 nurses (Atherton et al., 2023). Moreover, it has been calculated that 20% of UK economic growth between 1982 and 2005 derived from graduate skills accumulation (Holland et al., 2013). Despite higher education's evident importance, the literature on the impact of GenAI almost exclusively covers institutional concerns over the threats and opportunities of the new technology without exploring how its usage might affect students (as discussed in the literature review), missing a significant dimension of the sector.

To address this gap, we aim to answer the research question: **To what extent does generative AI usage affect students' relationships with their peers and teachers?** We employ a quantitative approach, utilising a questionnaire that operationalised usage as purpose and frequency and relations as avoidance and anxiety, measured via validated Likert-scale instruments (Fraley et al., 2011). We also adopt established measures for student perception of GenAI to understand its role as a factor (Chan and Chou, 2023). In doing so, we hope to bring attention to the largely ignored student perspective and broaden the higher education discourse regarding generative AI by seeing how students use it and its relation to their social and academic integration and involvement.
The following sections situate our research in the relevant literature and establish our methodology before discussing our survey results and findings and concluding with a consideration of future research directions and policy implications.

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2. Literature Review

2.1 Generative AI in Higher Education

For the most part, the discourse on GenAI in higher education is dominated by a focus on the technology's impacts and potential from the educational (teacher) and institutional (university) levels (Zawacki-Richter et al., 2019). Perhaps fuelled by media and popular interest (Insider), this has manifested as an intense fixation on GenAI's impact on academic integrity, especially regarding exams,

with little consideration for the student perspective (Sullivan et al., 2023). Many academic responses have even designated it a possible threat (Susnjak, 2022; Kwan Lo, 2023; Cotton et al., 2023). Within this context, some have also recognised potential pedagogical advantages to integrating such technologies. For example, Baidoo-Anu and Ansah (2023) suggests uses from automating essay marking to interactive/adaptive learning models whilst acknowledging possible limitations to its implementation.

Rarely, research does consider students' perception of GenAI, though this is often in dialogue with the above institutional discourse. Chan and Hu (2023) explore students' perceptions of GenAI, connecting this to their learning approach, outcomes, and user implementation. This is a starting point to think about how students use and understand GenAI. Chan and Chou (2023) extend this to show a strong correlation between positive perceptions of GenAI and the intention to use it. Munoz et al. (2023) find that students are more enthusiastic and interested in their education when using ChatGPT, revealing that students' perceptions and experiences can be valuable in testing the validity of the multitude of claims of GenAI being damaging/harmful. However, these studies are limited by their focus on GenAI's impact on education in a broad sense rather than students as individuals and by their presumption that GenAI usage by students is primarily focused on academic usage, an unvalidated claim.

Though it might be reasonable to think that GenAI would be predominantly used by students for academic purposes, given that this is students' primary use for technology overall, students also use it for various other reasons (Kvavik, 2005). Examining the type and frequency of GenAI usage by students remains essential as it is an understudied area that can reveal how students themselves are affected by the level of technological integration. Henry's (2012) study on the impacts of social media adoption on students' well-being and sense of community showed that frequency and type of usage are pertinent to the impact of technology and psychological distress, of which measures include high levels of avoidance and anxiety.

2.2 Interpersonal Relationships in Social Science

Within the social sciences, interpersonal relationships have long been considered a matter of primary significance, with many theories privileging it greatly. For Durkheim, an individual's actions are formed from the basis of a social structure, influenced and shaped by the society they are connected to (Durkheim, 1897). The field of social network analysis extends from this, seeking to harness these effects for productive uses (Borgatti et al., 2009). For instance, in management, social networks have been argued to boost organisational performance, mainly due to the sharing of knowledge and expertise (Cross, 2004).

In economics, these ideas have been expressed in terms of social capital, defined as a "a person's social characteristics – including social skills, charisma, and the size of his Rolodex – which enables him to reap market and non-market returns from interactions with others" (Glaeser et al., 2002, p. 438). Following Helliwell and Putnam (1999), Glaeser posits the relationship between education and social relationships to be "the most robust and the most important fact about the formation of human capital" (p. 16).

Beyond this, others have placed interpersonal relationships at the heart of identity formation, with Erikson (1968) viewing social context as both foundational to the production of identity in adolescents and to its development via self-expression in social interaction. Germane to this, Maslow places "love and affection and belongingness needs" (1943, p. 380) prominently as the third tier in his hierarchy of needs, reinforcing this notion of relationships being foundational in adolescence.

2.3 Significance of Interpersonal Relationships in Higher Education

Interpersonal relationships gain a further significance in higher education due to the student population being predominantly adolescent, one of their most formative periods in terms of identity construction (Erikson, 1968), whilst also undergoing a wide range of changes, such as adjusting to a new lifestyle and academic environment (Pittman and Richmond, 2008).

Interpersonal relationships as a virtue has found much emphasis in higher education research. For example, Hawkins and Weiss' (1985) social development model asserts the link between students having a positive social bond with their school and being more engaged in their studies and less likely to exhibit delinquent behaviour. Expanding on this theme, Hurtado and Carter (1997) highlight how lack of integration at university leads to dropout, whilst interestingly suggesting that peer conversations about course content outside of class improve their sense of belonging. This discourse on relationships echoes Maslow's notion of belongingness as a need, with Furrer and Skinner (2003) extending it to conclude that higher student relatedness leads to academic success and better emotional engagement. Moreover, Gillespie (2005) argues that "student–teacher connection emerges as a place of possibility" that allows students to flourish.

Relationships in higher education can thus be measured via a relationships structure framework (Fraley et al., 2011), as it has been demonstrated that the relationships that students form with their peers and teachers are emotionally laden, echoing the attachment theory (Bowlby, 1969; Garcia-Rodriguez et al., 2023) behind this construct. Given that gender is known to be a significant factor in subjective anxiety and behavioural avoidance (Mclean et al., 2010), which are aspects of a close relationship (Fraley et al., 2011) and pivotal to relationships in indicating one's likelihood to interact with others (Beatty, 2009), this must also be considered in relation to students' relationships.

2.4 Hypotheses

From this review of the literature, we concluded four hypotheses for how the usage of GenAI could be expected to affect students' interpersonal relationships:

1) *Students who use GenAI more frequently are less attached to their peers.*
2) *Students who use GenAI more frequently are less attached to their teachers.*
3) *Students who use GenAI for academic purposes are less attached to their peers.*
4) *Students who use GenAI for academic purposes are less attached to their teachers.*

3. Methodology

3.1 Self-Report Method and Design of Questionnaire

Self-report is among the most widely used measurement tools in psychology and social research (Haeffel and Howard, 2010). Respondents play an active role in data collection without external intervention, providing access to intrapsychic information such as thoughts, feelings, and sensations (Robins et al., 1999). This method is crucial for examining the experiential aspects of GenAI use among LSE students and its impact on their relationships with peers and instructors. Self-report also enhances validity as respondents tend to answer more diligently when reflecting on personal experiences (Robins et al., 2010). Conducting anonymous online questionnaires ensures data collection without social desirability bias, further enhancing the reliability of self-reported data.

We adopted two well-established Likert-scale instruments: the seven-point ECR-RS (Fraley et al., 2011) and the five-point EVT-based instrument (Chan and Chou, 2023). The ECR-RS, rooted in Bowlby's (1969) attachment theory, is designed for measuring close relationships. It has undergone extensive testing for construct validation on a large cohort of participants of 23,388 (Fraley et al., 2011). Our research focuses on participants' relationships with peers and instructors at LSE. The EVT-based instrument, proposed in 2023, has been successfully applied in diverse student populations (n = 879) in higher education institutions across India, Germany, Hong Kong, and the Netherlands (Chan and Chou, 2023).

Our questionnaire design utilises the Likert-scale format, enabling participants to express their levels of agreement or uncertainty for each statement. The questionnaire includes 16 five-point scale questions (Q4.1-Q5.4, see Appendix.1) derived from the EVT-based instrument, soliciting students' responses on motivation, perception, perceived value, perceived costs, knowledge, and frequency of GenAI use. The response options range from 1-Strongly Disagree to 5-Strongly Agree. In addition, the questionnaire features 18 seven-point scale questions (Q7.1-Q8.9, see Appendix.1) adapted from the ECR-RS, with response options ranging from 1-Strongly Disagree to 7-Strongly Agree. These questions aim to measure two theoretical factors: anxious and avoidant attachment (Rocha et al., 2017) within peer-to-peer and student-to-supervisor relationships at LSE. We also included an open text question to gain an insight into how students use GenAI.

3.2 Sampling

The sample for this study was drawn from the student population of LSE. A convenience sampling method was employed to reach a large number of LSE students efficiently, given the constraints of a two-week timeframe. The online questionnaire was shared through LSE online platforms and email, resulting in 105 responses over a three-day period. Our choice to focus on LSE was due both to convenience and the need to reduce the number of variables, such as quality of teaching and campus culture, that we would need to control for in an inter-university study.

3.3 Variables and Operationalisation

Description	Type	Name in dataset
The frequency of using generative AI	Independent, categorical	Frequency
The purpose of using generative AI	Independent, binary (0: non-academic, 1: academic)	Purpose_1
The intensity of peer-to-peer relationship	Dependent, continuous	Intensity
The intensity of student-to-instructor relationship	Dependent, continuous	Intensity1
Respondent's sex	Controlled, binary (0: Male, 1: Female)	Gender
Student's Perceived Cost of GenAI	Controlled, continuous	perception_cost

Student's Perceived Value of GenAI	Controlled, continuous	perception_value

Table 1: List of Variables Considered and Classifications

Due to the limitations of Natural Language Processing (NLP) methods like k-means clustering in accurately categorising the character variable "Purpose", a manual categorisation approach was used. This involved categorising the variable (labelled "Purpose_1") into two groups: academic-related and non-academic purposes. Samples with unknown purposes were excluded from the analysis for data quality and reliability.

Anxiety levels towards peers and instructors were assessed by averaging responses to specific items (Q7.7 to Q7.9 and Q8.7 to Q8.9, respectively). Avoidance towards peers was determined by averaging the values obtained from (Q7.6 + Q7.5 + (7-Q7.4) + (7-Q7.3) + (7-Q7.2) + (7-Q7.1))/6. Likewise, avoidance towards instructors was assessed using the average derived from (Q8.6 + Q8.5 + (7-Q8.4) + (7-Q8.3) + (7-Q8.2) + (7-Q8.1))/6.

To standardise the scale of anxiety and avoidance (see Figure 1), a transformation was applied by subtracting the median scale (4) from all data points. This standardised representation facilitated the construction of a diagram where anxiety was plotted on the x-axis and avoidance on the y-axis. By plotting the data points in this manner, we calculated the Euclidean distance between each point and the origin, thus quantifying the 'relationship intensity' of each data point. This intensity denotes the degree of attachment. Furthermore, samples could be categorised into four relationship types for further study.

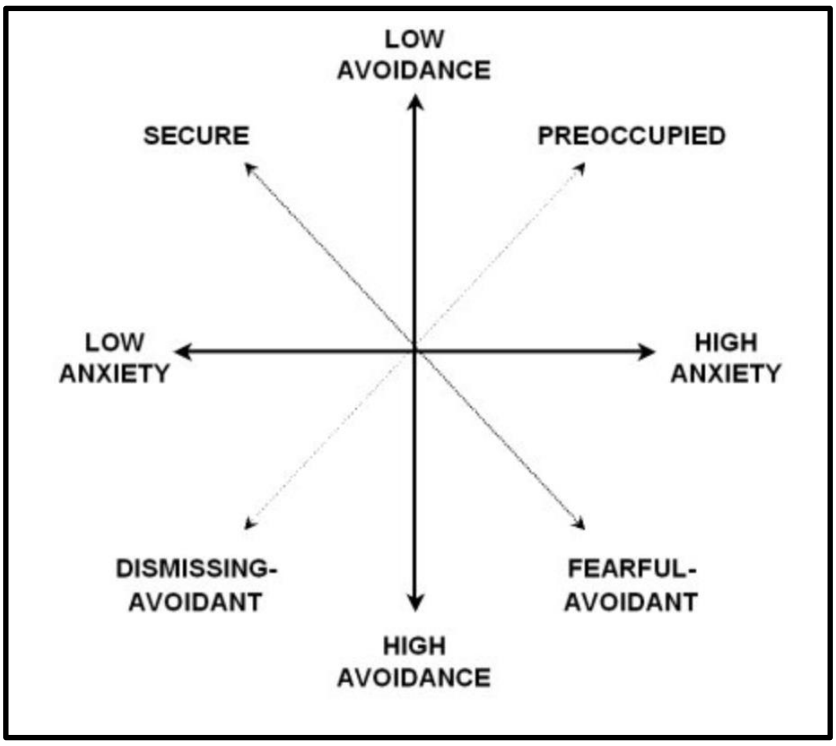

Figure 1. The two-dimensional model of individual differences in adult attachment

Aggregated variables perception value and perception cost were computed by summing responses to specific questions (Q4.1 to Q4.11 and Q5.1 to Q5.4, see in Appendix 1).

Subsequently, we conducted linear regression analyses on the relationship intensity for Peer-to-Peer and Peer-to-Instructor relationships since intensity values for both relationships are continuous variables. All independent and control variables were included as input factors, with a particular focus on the statistical significance and contribution of the independent variables, as indicated by their p-values.

4. Results

4.1 Overall regression model

Using Rstudio, we conducted linear regression analysis to examine the relationship intensity.
The following linear regression model was employed to investigate the associations:

$$y = \alpha + \beta_1 Purpose\_1 + \beta_2 Frequency + \beta_3 perception\_cost + \beta_4 perception\_value + \beta_5 Gender + \varepsilon$$

where:
α = *constant*
β_1 = *coefficient, i.e. ceteris paribus relationship between Purpose_1 (binary) and y*
β_2 = *coefficient, i.e. ceteris paribus relationship between Frequency (5 levels) and y*
β_3 = *coefficient, i.e. ceteris paribus relationship between the control perception_cost and y*
β_4 = *coefficient, i.e. ceteris paribus relationship between the control perception_value and y*
β_5 = *coefficient, i.e. ceteris paribus relationship between the control Gender and y*
ε = *error term*
(*set baselines in Appendix 2.1).*

4.2 Peer-to-Peer Relationship

The results of the regression analysis regarding the intensity of relationships in peer-to-peer contexts are presented in Table 1 of Appendix 2. None of the independent variables demonstrated statistically significant effects, as indicated by the *p*-values ($p > 0.05$). Consequently, the findings do not offer substantial support for the hypotheses under investigation. Control variable perception value appeared to be significant. Additionally, to evaluate potential multicollinearity, Variance Inflation Factor (VIF) values were examined in the regression model, as shown in Table 3 of Appendix 2. The analysis revealed no significant presence of multicollinearity among the variables. The suitability of the regression model for the provided dataset was verified by examining Residuals and Q-Q plots, as depicted in Figure 1 of Appendix 3.

4.3 Student-to-Instructor Relationship

Similar regression analysis was conducted for the student-instructor relationship, replacing the dependent variable with *Intensity1* (see Table 1). Table 4 in Appendix 2 presents the results of this regression. In this case, it was found that only Frequency level 2 (rarely) exhibited a statistically significant impact as an independent variable, with a coefficient of -1.48556. This coefficient suggests that a transition from Frequency level 1 (never) to level 2 would lead to a decrease in relationship intensity on the student-to-instructor relationship by approximately -1.48556 units. However, the sample size for level 2 is small (see Figure 2). Additionally, when considering the overall significance

of each variable through the ANOVA Type II test, as displayed in Table 5 of Appendix 2, none of the variables, including Frequency, were found to be significant. VIF values, presented in Table 6 of Appendix 2, indicate the absence of substantial multicollinearity. Assessment of the regression model's suitability for the dataset was performed using Residuals and Q-Q plots, as shown in Figure 2 of Appendix 3. These plots appeared to be less suitable compared to the regression model for peer-to-peer relationship intensity, as indicated in Figure 1 of Appendix 3, but overall still confirmed the model's adequacy. Therefore, we would state that the results are not statistically significant and we do not have sufficient evidence to support our stated hypotheses.

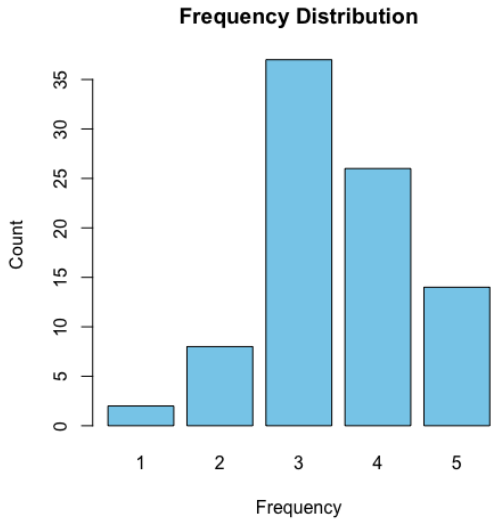

Figure 2. The distribution of responses: number of respondents in each Frequency level

5. Discussion

5.1 Further Exploration of Four Relationship Types

Although the relationship intensities are similar, the composition of the intensities varies remarkably, resulting in different types of relationships. To differentiate between the two, we depict our standardised dataset using visual representations, as illustrated in Appendix 4 and Figure 1. However, we reverse the avoidance axis to enhance clarity and interpretation.

The majority of respondents exhibit secure relationships with both their peers and instructors, whilst the least respondents demonstrate a fearful-avoidant relationship with both. It is worthwhile to mention that a considerable proportion of respondents exhibit a dismissing-avoidant relationship type with their instructors. There are two possible explanations but both require further investigation. Firstly, ChatGPT can potentially improve the independence and autonomy of autodidactic learners (Firat, 2023), which reduces students' need to seek help from their instructors, hence students reach out less but don't feel much anxiety. Secondly, the result might be specific to the LSE samples. The LSE's 2022 NSS survey results showed only 62% of students agreed that they received sufficient advice and support with their studies (NSS, 2022), possibly explaining their dismissing-avoidant relationship with their instructors.

Analysing Figure 3 to Figure 6 in Appendix 4, we observe that there is no discernible pattern concerning frequency and purpose, meaning that usage of GenAI is highly unlikely to have an impact on students' interpersonal relationships overall based on our dataset.

To further examine the differences in predicted probability of having different types of relationship, we created datasets varying one of the two independent variables (purposes / frequency) while holding the other constant. Given that the outcome variable (type of relationship) is non-interval and not ordered, we adopted the multinomial logistic regression.

For instance, holding frequency constant at "sometimes", the predicted probability of having a secure peer-to-peer relationship is 0.65 when using GenAI for academic purposes and is 0.35 for non-academic purposes. That is, people who use GenAI for academic purposes are more likely to have a secure relationship with their peers than for other purposes (e.g. using GenAI for casual conversation). Appendix 5 represents the full tables of predicted probability.

5.2 Limitations

Firstly, convenience sampling strategy may limit the representativeness of the wider population, suggesting that the findings might apply solely to our sample. For more generalisable results, future studies might consider systematic or stratified sampling methods. Nonetheless, the data procured is still valuable for examining this emerging topic.

Secondly, it is plausible that most responses manifest a central tendency bias (Douven, 2018), where individuals frequently opt for mid-scale options due to subjective evaluation. This is evident in the frequency scale (Figure 2), with the value of 3 being frequently chosen. The following graph demonstrates the distribution of responses and the prevalence of central tendency in our dataset.

Thirdly, the categorisation of the responses from the open-ended question entails subjective judgement and interpretation, potentially undermining the validity of our findings. Multiple responses with various implied meanings could further exacerbate this challenge.

Fourthly, our assumption that the intensity, rather than the type of relationship (Figure 1), would fluctuate in each relationship and might lead to a potential offset in our results. This is because certain variables could exert different directional effects on anxiety and avoidance, which an intensity measurement might not capture. Nonetheless, upon separately analysing anxiety and avoidance in both relationships, we found all independent variables to be insignificant (see Appendix 6). This suggests that this limitation should not significantly impact our findings, albeit possibly reducing their intricacy.

6. Conclusion

We find that there is no significant correlation between the frequency and purpose of GenAI usage and the intensity of both peer-to-peer and student-to-teacher relationships, indicating that GenAI use does not significantly impact students' interpersonal relationships. However, it was noted that their types of usage do have some bearing on the kinds of relationships students form with their peers and possibly with teachers. These findings argue against premature discussions of GenAI's negative influence on higher education from a student perspective. Indeed, it appears students gain benefits,

without experiencing probable negative impacts such as hindered development of self-identity and social capital formation. Additionally, unexpected yet enlightening findings related to types of relationships and the significance of perceptions have emerged, offering potential directions for future research.

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Appendix

Appendix.1: Question Survey

1. Which gender identity do you feel best represents you?
2. Have you used generative AI technologies like ChatGPT?
3. To what extent do you agree with the following statement: I have used generative AI technologies like ChatGPT. (1: never, 2: rarely, 3: sometimes, 4: often 5: most of the time)
4. To what extent do you agree with the following statements? (1: strongly disagree, 2: slightly disagree, 3: neutral, 4: slightly agree, 5: strongly agree)
    - 4.1. Students must learn how to use generative AI technologies well for their careers.
    - 4.2. I believe generative AI technologies such as ChatGPT can improve my digital competence.
    - 4.3. I believe generative AI technologies such as ChatGPT can improve my overall academic performance.
    - 4.4. I think generative AI technologies such as ChatGPT can help me become a better writer.
    - 4.5. I can ask questions to generative AI technologies such as ChatGPT that I would otherwise not voice out to my teacher.
    - 4.6. Generative AI technologies such as ChatGPT will not judge me, so I feel comfortable with it.
    - 4.7. I think AI technologies such as ChatGPT are a great tool for student support services due to anonymity.
    - 4.8. I believe generative AI technologies such as ChatGPT can help me save time.
    - 4.9. I believe AI technologies such as ChatGPT can provide me with unique insights and perspectives that I may not have thought of myself.
    - 4.10. I think AI technologies such as ChatGPT can provide me with personalized and immediate feedback and suggestions for my assignments.
    - 4.11. I think AI technologies such as ChatGPT is a great tool as it is available 24/7.
5. To what extent do you agree with the following statements? (1: strongly disagree, 2: slightly disagree, 3: neutral, 4: slightly agree, 5: strongly agree)
    - 5.1. Using generative AI technologies such as ChatGPT to complete assignments undermines the value of a university education.
    - 5.2. Generative AI technologies such as ChatGPT will limit my opportunities to interact with others and socialize while completing coursework.
    - 5.3. Generative AI technologies such as ChatGPT will hinder my development of generic or transferable skills such as teamwork, problem-solving, and leadership skills.
    - 5.4. I can become over-reliant on generative AI technologies.
6. What is your main use of GenAI, such as ChatGPT? (Open-ended question)
7. To what extent do you agree with the following statements? (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neutral, 5: Somewhat agree, 6: Agree, 7: Strongly disagree)
    - 7.1. It helps to turn to my friends in times of need.
    - 7.2. I usually discuss my problems and concerns with my friends.
    - 7.3. I talk things over with my friends.
    - 7.4. I find it easy to depend on my friends.
    - 7.5. I don't feel comfortable opening up to my friends.

7.6. I prefer not to show my friends how I feel deep down.
7.7. I often worry that my friends doesn't really care for me.
7.8. I'm afraid that my friends may abandon me.
7.9. I worry that my friends won't care about me as much as I care about him or her.

8. To what extent do you agree with the following statements? (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neutral, 5: Somewhat agree, 6: Agree, 7: Strongly disagree)
8.1. It helps to turn to my instructors in times of need.
8.2. I usually discuss my problems and concerns with my instructors.
8.3. I talk things over with my instructors.
8.4. I find it easy to depend on my instructors.
8.5. I don't feel comfortable opening up to my instructors.
8.6. I prefer not to show my instructors how I feel deep down.
8.7. I often worry that my instructors doesn't really care for me.
8.8. I'm afraid that my instructors may abandon me.
8.9. I worry that my instructors won't care about me as much as I care about him or her.

Appendix 2: Raw Statistical Data *(Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)*

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.583742	0.860106	1.841	0.0694
Purpose_11	-0.305433	0.236255	-1.293	0.1999
Frequency2	0.002185	0.766087	0.003	0.9977
Frequency3	0.374810	0.717936	0.522	0.6031
Frequency4	-0.105560	0.735853	-0.143	0.8863
Frequency5	0.191955	0.772586	0.248	0.8044
perception_cost	-0.031881	0.033281	-0.958	0.3411
perception_value	0.035888	0.017169	2.090	0.0399*
Gender2	-0.317032	0.235774	-1.345	0.1826

Table 1 - regression model against relationship intensity on Peer-to-Peer summary (Multiple R-squared: 0.1342,Adjusted R-squared: 0.04544)

Response	**Sum Sq**	**Df**	**F value**	**Pr(>F)**
Purpose_1	1.512	1	1.6714	0.19989
Frequency	3.467	4	0.9584	0.43518
perception_cost	0.830	1	0.9176	0.34106
perception_value	3.951	1	4.3690	0.03986*
Gender	1.635	1	1.8081	0.18264
Residuals	70.541	78		

Table 2 - Anova test (Type II tests) on regression on relationship intensity on Peer-to-Peer

Variable	GVIF	GVIF$^{(1/(2\cdot Df))}$
Purpose_1	1.044255	1.021888
Frequency	1.691470	1.067906
perception_cost	1.217415	1.103365
perception_value	1.675314	1.294339
Gender	1.040000	1.019804

Table 3 - VIF on regression on relationship intensity on Peer-to-Peer

	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	2.51328	0.80651	3.116	0.00256 **
perception_cost	-0.03024	0.03121	-0.969	0.33549
perception_value	0.02512	0.01610	1.560	0.12277
Gender2	-0.36084	0.22108	-1.632	0.10667
Purpose_11	-0.11128	0.22153	-0.502	0.61686
Frequency2	-1.48556	0.71835	-2.068	0.04195 *
Frequency3	-0.80793	0.67320	-1.200	0.23372
Frequency4	-0.81000	0.69000	-1.174	0.24401
Frequency5	-0.72563	0.72445	-1.002	0.31962

Table 4 - regression model against relationship intensity on student-to-instructor summary (Multiple R-squared: 0.1551,Adjusted R-squared: 0.06844)

Response	Sum Sq	Df	F value	$\Pr(>F)$
perception_cost	0.747	1	0.9392	0.3355
perception_value	1.936	1	2.4341	0.1228
Gender	2.118	1	2.6640	0.1067
Purpose_1	0.201	1	0.2523	0.6169
Frequency	4.499	4	1.4145	0.2370
Residuals	62.024	78		

Table 5 - Anova test (Type II tests) on regression on relationship intensity on student-to-instructor

	GVIF	$\text{GVIF}^{(1/(2*Df))}$
perception_cost	1.217415	1.103365
perception_value	1.675314	1.294339
Gender	1.040000	1.019804
Purpose_1	1.044255	1.021888
Frequency	1.691470	1.067906

Table 6 - VIF on regression on relationship intensity on student-to-instructor

Appendix 2.1: Baselines

The baseline level for the variable "Gender" was set as 1 (Male).
The baseline level for the variable "Frequency" was set as 1 (Never).
The baseline level for the variable "Purpose_1" was set as 0 (Non-Academic).

Appendix 3: Fitness of Regression Model

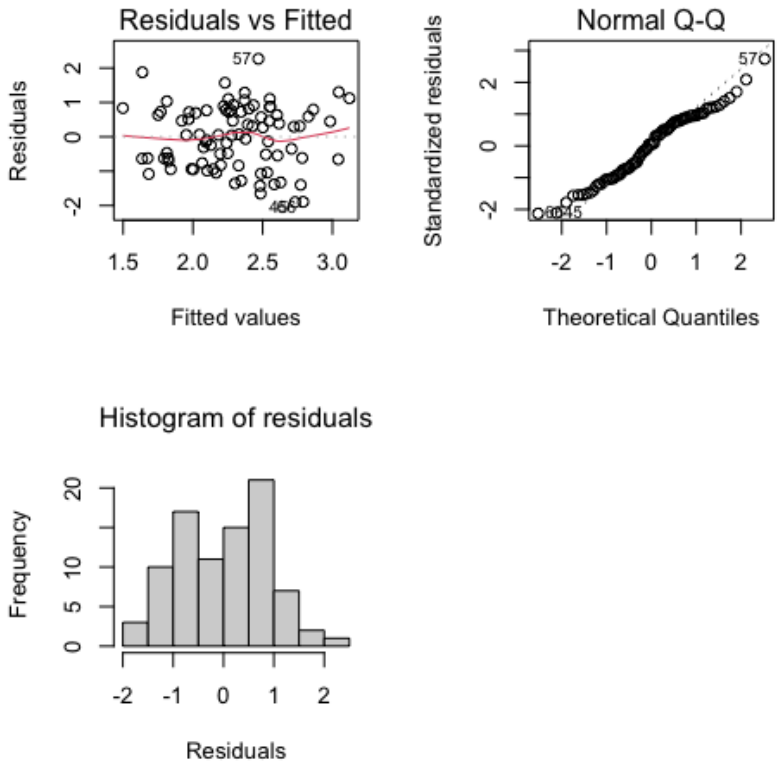

Figure 1 - Residuals and Q-Q plots on Peer-to-Peer relationship intensity

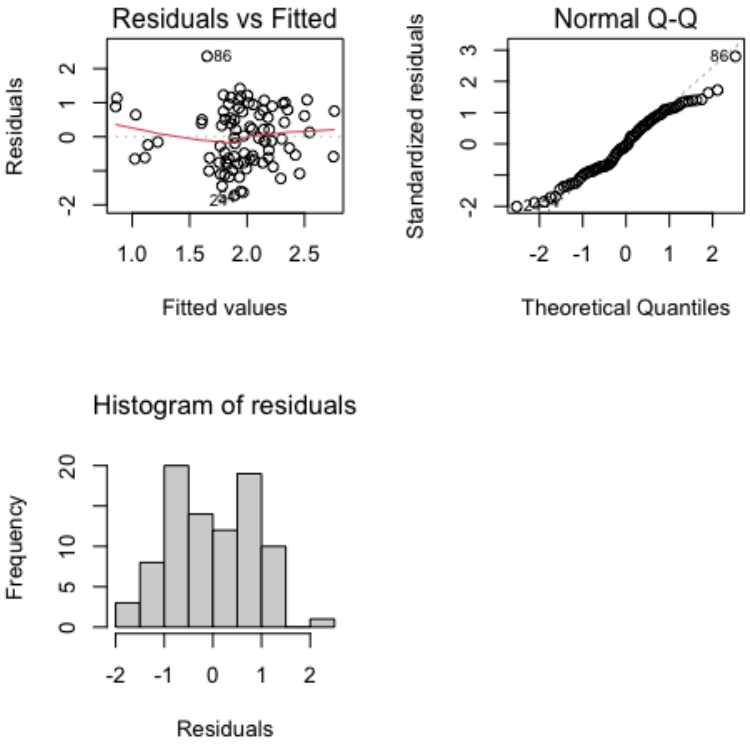

Figure 2 - Residuals and Q-Q plots on students to instructors relationship intensity

Appendix 4: ECR-RS plots

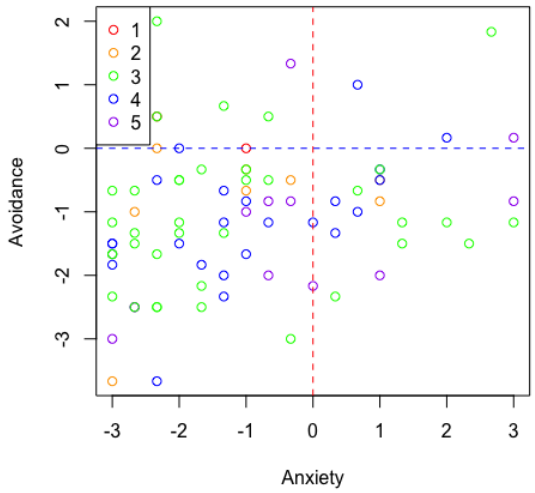

Figure 3 - Scatter Plot of Anxiety and Avoidance for peer-to-peer according to Frequency levels

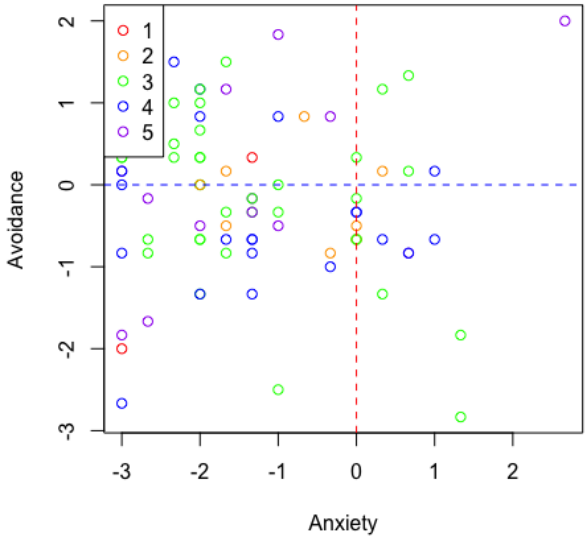

Figure 4 - Scatter Plot of Anxiety and Avoidance for student-to-instructor according to Frequency levels

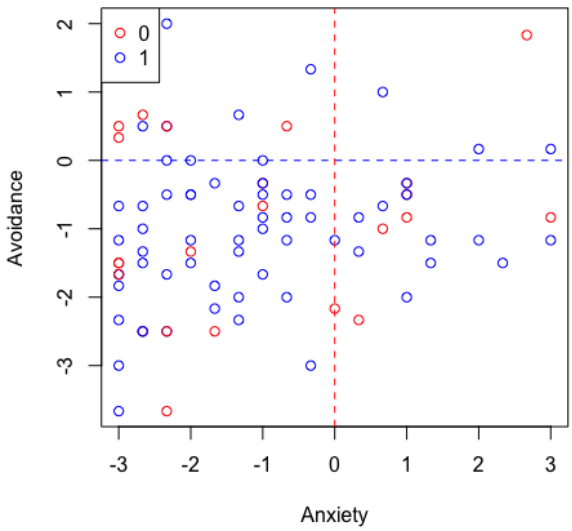

Figure 5 - Scatter Plot of Anxiety and Avoidance for peer-to-peer according to Purpose_1

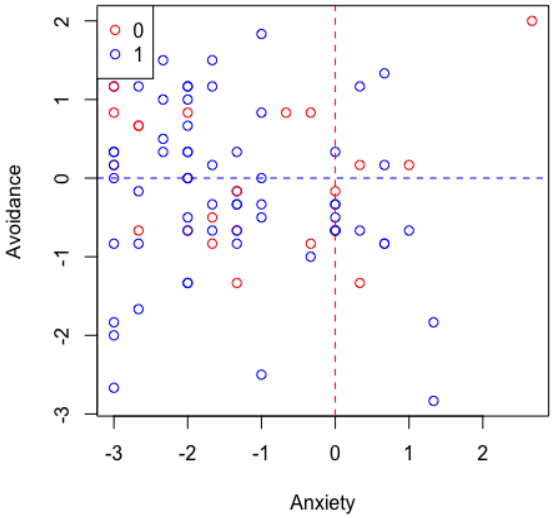

Figure 6 - Scatter Plot of Anxiety and Avoidance for student-to-instructor according to Purpose_1

Appendix 5: Predicted Probability Table

Purpose/Type	Secure	Dismissing-avoidant	Fearful-avoidant	Preoccupied
Non-academic	0.3518895	0.29252341	0.01010815	0.3454789
Academic	0.6532101	0.07688732	0.01032751	0.2595750

Table 7 - the predicted probability of having different types of relationship between peers given the different purposes (hold the frequency constant at "sometimes")

Frequency/Type	Secure	Dismissing-avoidant	Fearful-avoidant	Preoccupied
1	3.624175e-17	7.952695e-01	7.611849e-22	1.187527e-22
2	6.023631e-01	7.465805e-11	8.030829e-18	2.126266e-01
3	6.532101e-01	7.688732e-02	1.032751e-02	2.595750e-01
4	5.810440e-01	4.893920e-02	4.943864e-02	2.058278e-01
5	6.052518e-01	4.978382e-02	2.409072e-02	1.529099e-01

Table 8 - the predicted probability of having different types of relationship between peers given the different frequency (hold the purpose constant at "academic")

	Secure	Dismissing-avoidant	Fearful-avoidant	Preoccupied
Non-academic	0.1866332	0.4268670	0.28699198	0.01369925
Academic	0.2154587	0.3793623	0.08917367	0.03403150

Table 9 - the predicted probability of having different types of relationship between students and instructors given the different purposes (hold the frequency constant at "sometimes")

Frequency/Type	Secure	Dismissing-avoidant	Fearful-avoidant	Preoccupied
1	0.6099776	0.3900220	2.923533e-07	5.074189e-08
2	0.1733388	0.1956694	4.880156e-02	1.229193e-18
3	0.2154587	0.3793623	8.917367e-02	3.403150e-02
4	0.3620209	0.3148436	2.501548e-02	1.233512e-01
5	0.5162532	0.3684805	5.010358e-02	6.516272e-02

Table 10 - the predicted probability of having different types of relationship between students and instructors given the different frequency (hold the purpose constant at "sometimes")

Appendix 6: Regression on Anxiety and Avoidance

Variable	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	0.838672	1.527580	0.549	0.5846
perception_cost	0.102787	0.059109	1.739	0.0860
perception_value	-0.001398	0.030494	-0.046	0.9635
Gender2	0.702028	0.418742	1.677	0.0976
Purpose_11	0.008787	0.419598	0.021	0.9833
Frequency2	0.600725	1.360598	0.442	0.6601
Frequency3	0.393545	1.275081	0.309	0.7584
Frequency4	0.440357	1.306902	0.337	0.7371
Frequency5	0.808861	1.372141	0.589	0.5572

Table 11 - regression on peer-to-peer anxiety

Variable	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	1.220048	1.206563	1.011	0.315
perception_cost	0.051309	0.046687	1.099	0.275
perception_value	-0.008812	0.024085	-0.366	0.715
Gender2	0.421135	0.330745	1.273	0.207
Purpose_11	0.024014	0.331421	0.072	0.942
Frequency2	1.440152	1.074672	1.340	0.184
Frequency3	0.840150	1.007126	0.834	0.407
Frequency4	0.724691	1.032260	0.702	0.485
Frequency5	0.857204	1.083789	0.791	0.431

Table 12 - regression on student-to-instructor anxiety

Variable	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	4.17898	1.01868	4.102	9.97e-05 ***
perception_cost	0.03074	0.03942	0.780	0.4379
perception_value	-0.01981	0.02033	-0.974	0.3329
Gender2	0.46795	0.27924	1.676	0.0978 .
Purpose_11	-0.09799	0.27981	-0.350	0.7271
Frequency2	-1.16117	0.90733	-1.280	0.2044
Frequency3	-1.09380	0.85030	-1.286	0.2021
Frequency4	-0.93868	0.87152	-1.077	0.2848
Frequency5	-1.18191	0.91503	-1.292	0.2003

Table 13 - regression on peer-to-peer avoidance

Variable	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	3.611142	0.893586	4.041	0.000124 ***
perception_cost	-0.099373	0.034577	-2.874	0.005221 **
perception_value	0.009549	0.017838	0.535	0.593957
Gender2	0.378491	0.244951	1.545	0.126353
Purpose_11	-0.290578	0.245452	-1.184	0.240067
Frequency2	0.805197	0.795907	1.012	0.314823
Frequency3	1.086714	0.745882	1.457	0.149144
Frequency4	0.819309	0.764496	1.072	0.287161
Frequency5	1.099485	0.802659	1.370	0.174679

Table 13 - regression on student-to-instructor avoidance