Part 1

1. The study included a total of 222 participants. In terms of ethnicity, the majority of students identified as Caucasian/White at 51.4%, followed by Latino/Hispanic at 27.9%, African American/Black at 10.4%, Asian/Asian American at 6.3%, and Native American, Native Hawaiian, or Pacific Islander at 4.1%. In terms of gender, 69.4% of participants identified as female, 27.9% as male, and 2.7% as non-binary or third gender. When examining the student's class rank, most participants were sophomores at 49.1%, followed by freshmen at 25.2%, juniors at 20.3%, and seniors at 5.4%. The mean age of participants was 20.64 years, with a standard deviation of 1.44, showing that the sample was rather consistently young. Lastly, concerning device usage, 55.4% of participants used iOS devices, while 44.6% used Android devices.
2. Based on the independent samples T-test used, we can see that there is a significant difference in perceptions of privacy from IOS to Android users. The T and P values are 3.23 and 0.014, with a value less than 0.05, which means that this data is statistically significant. Based on this data iOS users are more likely than Android users to use location-based services without privacy concerns for everyday convenience. The descriptive statistics are M = 6.453, SD = 1.285 for IOS users and M = 3.841, SD = 1.494 for Android users.
3. Based on the independent samples T-test used, we can see that there is a significant difference in usage perceptions from Android to iOS users. The T and P values are -2.03 and 0.041, with a value less than 0.05, which means that this data is statistically significant. Based on this data, Android users are more likely than iOS users to perceive location-based technology as helping them accomplish tasks more quickly. The descriptive statistics are M = 5.318, SD = 1.411 for Android users and M = 2.287, SD = 1.278 for iOS users.
4. Based on the independent samples T-test used, we can see that there is a significant difference in awareness of terms and conditions from iOS to Android users. The T and P values are 1.942 and 0.041, with a value less than 0.05, which means that this data is statistically significant. Based on this data, iOS users are more aware of the terms and conditions of the websites or apps they use compared to Android users. The descriptive statistics are M = 5.886, SD = 1.685 for iOS users and M = 4.810, SD = 1.716 for Android users.
5. Based on the independent samples T-test used, we can see that there is a significant difference in the understanding of data being used for marketing purposes from Android to iOS users. The T and P values are 2.99 and 0.001, with a value less than 0.05, which means that this data is statistically significant. Based on this data, Android users are more likely than iOS users to understand that their data is being used for marketing purposes. The descriptive statistics are M = 6.054, SD = 1.455 for Android users and M = 3.976, SD = 1.194 for iOS users.
6. Based on the one-way ANOVA test used, we can see that there is a significant difference in privacy perceptions vs. everyday convenience among the types of location-based applications. The F and P values are 3.984 and 0.041, with a value less than 0.05, which means that this data is statistically significant. Based on this data, users of Maps applications report the highest acceptance of using location-based services

despite privacy concerns, followed by RideShare users, and then E-Commerce users. The descriptive statistics are M = 6.187, SD = 1.180 for Maps, M = 5.921, SD = 1.170 for RideShare, and M = 1.911, SD = 0.994 for E-Commerce.

7. Based on the one-way ANOVA test used, we can see that there is a significant difference in usage perceptions (i.e., perceptions of quickness) among the types of location-based applications. The F and P values are 7.768 and 0.031, with a value less than 0.05, which means that this data is statistically significant. Based on this data, users of Maps applications perceive the highest level of quickness, followed by RideShare users, and then E-Commerce users. The descriptive statistics are M = 6.277, SD = 1.012 for Maps, M = 5.030, SD = 0.775 for RideShare, and M = 2.067, SD = 0.984 for E-Commerce.
8. Based on the one-way ANOVA test used, we can see that there is no significant difference in awareness of terms and conditions among the types of location-based applications. The F and P values are 1.966 and 0.451, with a value greater than 0.05, which means that this data is not statistically significant. Based on this data, users of different types of location-based applications do not significantly differ in their awareness of terms and conditions. The descriptive statistics are M = 6.409, SD = 1.287 for E-Commerce, M = 5.140, SD = 1.234 for RideShare, and M = 4.993, SD = 1.284 for Maps.
9. Based on the one-way ANOVA test used, we can see that there is a significant difference in the understanding that data is being used for marketing purposes among the types of location-based applications. The F and P values are 8.936 and 0.002, with a value less than 0.05, which means that this data is statistically significant. Based on this data, Maps users have the highest understanding, followed closely by RideShare users, with E-Commerce users having the lowest understanding. The descriptive statistics are M = 6.012, SD = 0.991 for Maps, M = 5.978, SD = 0.967 for RideShare, and M = 1.915, SD = 1.101 for E-Commerce.
10. Based on the correlation test used, we can see that there is a statistically significant relationship between college years and perceptions of privacy (i.e., against everyday convenience) of location-based technology. The correlation coefficient and p-value are $r = -0.069$ and $p = 0.0396$, with a value less than 0.05, which means that this data is statistically significant. Based on this data, as students go through college years, their perception of privacy decreases in favor of everyday convenience when using location-based services. However, the strength of this relationship is relatively weak.
11. Based on the linear regression analysis used, we can see that awareness of terms and conditions significantly predicts an understanding that data is being used for marketing purposes. The F and P values are 7.164 and 0.001, with a value less than 0.05, which means that this data is statistically significant. The model also shows a moderate relationship, with $R = 0.500$ and $R^2 = 0.2500$, indicating that approximately 25% of the variance in the understanding of data used for marketing can be explained by awareness of terms and conditions. Based on this data, participants who are more aware of terms and conditions are more likely to understand that their data is being used for marketing purposes.

12. Based on the linear regression analysis used, we can see that understanding that data is being used for marketing purposes significantly predicts perceptions of privacy against the everyday convenience of location-based technology. The F and P values are 26.011 and <.001, with a value less than 0.05, which means that this data is statistically significant. The model shows a very strong relationship, with $R = 0.764$ and $R^2 = 0.5837$, indicating that approximately 58.37% of the variance in privacy perceptions can be explained by understanding of data use for marketing. Based on this data, participants who understand that their data is being used for marketing purposes are more likely to use location-based services despite privacy concerns.

Part 2

The findings from this study show several key relationships between user demographics, operating systems, and attitudes toward location-based technology. iOS users were much more likely to use location-based services despite privacy concerns and showed greater awareness of terms and conditions, while Android users demonstrated a stronger understanding that their data is being used for marketing and thought of these services as more useful for being efficient. Additionally, perceptions of location-based applications varied widely by app type: Maps and RideShare apps were associated with more user satisfaction with convenience and understanding of data use, whereas E-Commerce apps consistently scored lower. There was also a meaningful relationship between college years and privacy perceptions, as well as predictive links between awareness of terms and understanding of marketing data use, and between understanding of data use and comfort with privacy trade-offs.

Practitioners should look at these patterns when designing or marketing location-based applications. Applications that are used for everyday utility, like Maps and RideShare, appear to enjoy higher user trust and satisfaction, which may be due to the clear benefits they provide. In contrast, E-Commerce apps may need to work harder to establish credibility and value around data usage, as it is not necessary. Developers should ensure these applications clearly explain how data improves the user experience and make privacy-related information accessible and relevant. Building this transparency may help shift user perception, especially for apps perceived as less essential or more commercial.

My recommendations include embedding privacy communication into user flows, particularly for Android users who appear more sensitive to marketing data use. Developers should also frame data collection around benefits, especially since users who understand how their data is used tend to be more accepting of privacy trade-offs. Tailoring user education to class year or tech experience could also improve response, as older students showed slightly reduced privacy concerns. Ultimately, location-based apps that offer a clear purpose, explain data collection transparently, and demonstrate respect for user privacy are more likely to earn user trust and encourage use across diverse user groups.