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Examining the Effect of Customer Perceived Health Risk and Acceptance on Contactless Hotel Application Usage During the Pandemic

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Abstract

During the COVID-19 pandemic, this study looks at the effects of contactless hotel applications, how customers accept them, and what they think the health risks are. The hotel business is part of the hospitality industry, which focuses on giving people places to stay. In recent years, more and more people around the world have started to see travel as an important part of their lives. The global hotel and resort market was worth 1.21 trillion US dollars in 2019. This is a reasonable drop from the 1.24 trillion US dollars it was worth the year before due to a pandemic announced by the World Health Organization (WHO). So, there needs to be a new way to stay in business so that people can try out new business ideas during COVID-19 and the social distance. So, two research questions were made, the first of which will look at how contactless hotel apps affect how customers feel about them. Also, the second question will look at how customers' perceptions of health risks affect the relationship between contactless applications and customers' acceptance of them.

Keywords: Contactless Hotel Applications, Perceived Health Risks, COVID-19 Pandemic, Customer Acceptance

Introduction

The hotel industry is a subset of the hospitality sector primarily concerned with supplying consumers with various lodging services (Le & Phi, 2021). There are many distinct types of hotels, which can be categorized according to factors such as their size, purpose, level of service, and cost. There is a possibility that certain clients are better knowledgeable about the star rating system, in which a score of one is the lowest, and a score of five is the highest. In addition, a variety of functions, including those associated with businesses, casinos, spas, extended stays, bed and breakfasts, and other categories, are available. Over the course of

the past few decades, an ever-increasing number of people all over the world have started to recognize the importance of travel as a fundamental component of their lives (Brem et al., 2021). In 2019, the size of the global hotel and resort market was 1.21 trillion US dollars, which is a moderate reduction from the size of the industry in 2018. 1.24 trillion US dollars was reached in 2018. Despite this, the industry was anticipated to be worth 1.22 trillion USD in 2021 (Powell, 2020). Still, the market share has been lowered up to some value as a result of the pandemic that was proclaimed by the World Health Organization (WHO).

The data from the year 2017 showed positive growth for the hotel industry in Malaysia, which recorded 66.1% (Council), as the markets of the Association of Southeast Asian Nations (ASEAN) continued to contribute largely with the arrivals, coming from countries such as Singapore, Indonesia, Brunei, and Thailand (Hirschmann, 2020). Because of the Coronavirus outbreak in Wuhan City, located in Hubei Province, China, the occupancy rate of hotels in Malaysia will begin to drop to 59.9% in the year 2019. As a result, the occupancy rate of hotels will plummet to 25.1% in the year 2020. In addition, the World Health Organization classified the outbreak as a pandemic on March 11, 2020, which prompted Malaysia to shut down its international borders beginning in March of that same year.

The pandemic caused by the coronavirus (Covid-19) not only had a big influence on the general public's health but it also had a significant impact on the tourism and hotel industries, which are two of the most important industries in the world (Wosik et al., 2020). Beginning in the early part of 2020, there was a significant decrease in travel throughout the world as a result of the widespread implementation of curfews and other travel restrictions by many nations in an effort to stop the spread of the virus. The hotel industry was the sector that suffered the most financially as a result of the coronavirus (Ye et al., 2020). It is anticipated that the revenue generated by the travel and tourism industry will decrease from 711.94 billion US dollars in 2020 to 568.6 billion US dollars in 2030, representing a loss of more than 20%. (Lock, 2021) As a result of the established curfews and travel restrictions to halt the spread of the virus, international travel began to diminish substantially at the beginning of the year 2020. The hotel industry was the sector that suffered the most financially as a result of the coronavirus (Ye et al., 2020).

The move toward providing a contactless experience for guests is gaining momentum at a rapid rate. As a result of this, several hotels all over the world have begun to implement technological solutions to streamline the check-in, in-room, and checkout processes for their guests. As people become more conscious of the potential dangers that are associated with physical contact and touch, COVID-19 has contributed significantly to the widespread adoption of contactless technology. Because of this, hotel owners are making investments in new and imaginative methods to provide their customers with a hands-free experience. On the other hand, the concept of contactless hotel experiences is not a completely novel one. Many companies that operate in the hospitality sector have, over the course of the past few years, been utilizing technologies such as Smartphone door locks, immediate communication, and other forms of self-service software.

The vast majority of hotels have implemented contactless applications, such as online booking, QR codes, electronic menus in restaurants, and radio frequency identification (RFID) devices, such as keyless room admission (Bonfanti et al., 2021). As a result, in order to keep

operations running smoothly during the Covid-19 pandemic, the management of the hotel has implemented a number of contactless application services. These services include a QR menu in the room for use when placing orders, an RFID door lock, check-in and check-out applications, and check-in and check-out applications (Varga et al., 2021). In addition, the current study highlighted how customers would accept and use contactless applications while considering the potential risks to their health. This research looked into the customers' adoption of the application during the Covid-19 conference as well as how their worries about the health dangers associated with staying in hotels influenced their behaviour.

Literature Review

The current chapter consisted of a literature assessment of contactless applications that were applied in the hotel business, technology-assisted gadgets, perceived health hazards, perceived acceptability of technology-assisted applications, a theoretical framework, and hypotheses of the proposed framework. As a consequence of this, a variety of research journals, articles, reports, newspapers, and electronic publications were investigated in order to investigate the relationship between contactless applications and customers' perceptions of the risks to their health as well as the level of acceptance customers have for these applications. In addition, this chapter described the notion of proposed relationship and covered it from three different broad viewpoints for the purpose of gaining detailed insights into the subject matter of the research.

Technology, its Definition and Conceptualization

As a direct consequence of the second industrial revolution, widespread adoption of many forms of technology occurred in the 20th century. Theories of technological change and innovation try to understand the factors that affect technological innovation and the influence that technology has on society and culture. Similarly, the linear model of technological innovation and technological determinism are debunked by some of the most recent theories of technological change (Dragovi et al., 2018). These two theories of how technological development occurs are the technological determinism and the linear model of technological innovation. Some contemporary technological change and innovation theories challenge the linear model by pointing to the history of technology. There, they find evidence that technological innovation frequently leads to new scientific fields and emphasize the important role that social networks and cultural values play in creating and shaping technological innovation. These theories challenge the linear model because they highlight the importance of social networks and cultural values in the creation and shaping of technological innovation (Zhou et al., 2021).

Technology Related Models

Technology evolves much faster than the media or institutions that consumers have traditionally relied on to inform and enforce their decisions. The rate at which technology evolves is unpredictably fast.

Technology Acceptance Model (TAM)

In both their personal and professional lives, people's attitudes toward and utilization of technology make up what is known as the "technology acceptance model" (TAM). In a similar vein, most technologies in countries like Malaysia are primarily employed in hotels to generate reports in the food and beverage and front office departments but are not being

used to their full extent. Therefore, as this epidemic develops, most hotels are implementing new technological innovations to attract clients worldwide. While this may sound like a great idea in theory, there are a number of concerns that need to be addressed before a hotel kiosk can get widespread acceptance among its target audience (Dhagarra et al., 2020). It may be obvious to researchers that clients who are unaware of their health status and who use kiosks for self-service are taking a risk (Lee, 2018). Additionally, not all guests are enthusiastic about using the hotel's self-service kiosk for its contactless application.

Findings

Quality of the constructs in the study is assessed based on the evaluation of the measurement model. First, the validity and reliability of the measurement model is assessed then the structural model is validated. The measurement of the quality starts with evaluation of the factor loadings which is followed by establishing the constructs' reliability and constructs validity. As discussed, the validity and reliability of the measurement model is evaluated by assessing the following.

i) Internal consistency reliability
ii) Indicator reliability
iii) Convergent validity
iv) Discriminant validity

Table 3.1 presents the results for all research variables items like customer acceptance, perceived risks to customer acceptance, customer usage of contactless applications and its analysis to evaluate the validity and reliability of the measurement model. Examining the individual indicator loadings is the first stage in model evaluation. It calculates relationship estimations and determines an item's absolute contribution to its assigned construct. It is desirable that loadings exceed 0.7, as this implies that the construct explains more than 50% of the variance in the indicator, suggesting that the indicator is reliable (Hulland, 1999). The indicator loadings scores in Table 3.1 are between 0.700 and 0.800, which are higher than the recommended value (0.7), implying a high level of reliability.

Table 3.1
Factor Loadings, Cronbach's Alpha, Composite Reliability

	Outer Loadings	Cronbach's Alpha	Composite Reliability	AVE
Ease of Use		0.883	0.915	0.684
PEU1	0.717			
PEU2	0.848			
PEU3	0.823			
PEU4	0.851			
PEU5	0.888			
Perceived Health Risk		0.891	0.917	0.649
PRCA2	0.812			
PRCA2	0.840			
PRCA3	0.841			
PRCA4	0.842			
PRCA5	0.707			
PRCA6	0.783			
Customer Usage		0.763	0.864	0.679
CU3	0.805			
CU4	0.804			
CU5	0.861			

As part of the measurement model evaluation, 3 items (Health Risk 7, Usage 1, Usage2) were removed from the analysis because of low factor loadings. To the reliability constructs, the study used Cronbach's alpha and composite reliability (CR). All CR were higher than the recommended value of 0.700 (Wasko & Faraj, 2005). Cronbach's alpha of each construct exceeds the 0.700 threshold. These results indicate that the items used to represent the construct poses satisfactory internal consistency reliability. The indicator reliability of the measurement model is measured by examining the item loadings. A measurement model is said to have a satisfactory indicator reliability when each item's loading estimates is higher between 5 -7 (Hair et al., 2017). Based on the analysis, all items in the measurement model exhibited loadings exceeding 0.5, ranging from lower bound of 0.707 to an upper bound of 0.888. All items are significant at the level of 0.001. Thus, all items used for this research demonstrate satisfactory indicator reliability.

Convergent and Discriminant Validity

As part of the measurement model evaluation, 30 item (list of items) were removed from the analysis because of low factor loadings. To the reliability constructs, the study used Cronbach's alpha and composite reliability (CR). All composite reliability was higher than the recommended value of 0.700 (Wasko & Faraj, 2005). Cronbach's alpha of each construct exceeds the 0.700 thresholds. The AVE must be at least 0.50, indicating that the construct explains 50% or more of the variance among the components that make up the construct. Convergent validity was acceptable because the average variance extracted (AVE) was over 0.500 (Hair et al., 2017). The result for reliability and validity along with the factor loading for the items are presented in the Table 3.2 under the ambit of Fornell-lackers criterion. Hence, the result of convergent validity was acceptable because the average variance extracted (AVE) was over 0.50.

Table 3.2
Fornell-Lackers criterion

	Ease of Use	Contactless Usage	Perceived Risk to Customer Acceptance
Ease Of Use	0.827		
Contactless Usage	0.754	0.824	
Perceived Risk to Customer Acceptance	0.6	0.62	0.806

Note: Value in Italic represent square-root of AVE

The discriminant validity of the construct must be evaluated to ensure that it does not correlate with other constructs. In PLS-SEM, the heterotrait-monotrait ratio of correlations (HTMT) is a new method for evaluating discriminant validity. Moreover, it was argued that this technique performs better, as evidenced by the Monte Carlo simulation study. In comparison to the cross-loadings criterion, the simulation revealed that HTMT will offer higher specificity and sensitivity rates (Henseler et al., 2015). It was highlighted by the Monte Carlo simulation analysis research work, Henseler et al (2015) advocate for this method's greater performance. When HTMT was compared to the cross-loadings criterion, the simulation revealed that it would produce greater specificity and sensitivity rates as reported in Table 3.3.

Table 3.3
HTMT Ratio

	Ease of Use	Contactless Usage	Perceived Risk to Customer Acceptance
Ease of Use			
Contactless Usage	0.91		
Perceived Risk to Customer Acceptance	0.666	0.751	

Cross Loadings

Researchers highlighted that cross loading is another technique to verify for discriminant validity at the indicator stage (Henseler et al., 2015). Each indicator should have a higher loading on the construct it is supposed to monitor, and all measuring indicators are loaded higher than other construct's indicators, as seen in Table 4.12. Consequently, the loading indicates that the model's discriminant validity has been achieved. The current study's finding indicates that all measures in the path model are valid and reliable; it is time to move on to the next step. This entails evaluating the structural model to identify the importance of the links and hypotheses that have been generated (Henseler et al., 2015). Furthermore, no additional items were discarded because the values were significantly higher than the specified minimum value.

Table 3.4
Cross-Loadings

	ACPT	Moderating Effect 1	PHR	CU
PEU1	0.717	-0.395	0.431	0.674
PEU2	0.848	-0.32	0.504	0.587
PEU3	0.823	-0.285	0.523	0.6
PEU4	0.851	-0.405	0.448	0.584
PEU5	0.888	-0.361	0.564	0.654
Contactless Usage * Perceived Risk to CA	-0.429	1	-0.471	-0.44
PRCA1	0.506	-0.391	0.812	0.439
PRCA2	0.474	-0.379	0.84	0.576
PRCA3	0.512	-0.447	0.841	0.611
PRAC4	0.439	-0.294	0.842	0.547
PRAC5	0.536	-0.422	0.707	0.434
PTAC6	0.395	-0.302	0.783	0.369
CU3	0.668	-0.36	0.428	0.805
CU4	0.601	-0.337	0.547	0.804
CU5	0.585	-0.395	0.566	0.861

PEU: Perceived Ease of Use PRCA: Perceived Risk to Customer Acceptance CU: Customer Usage

Variance Inflation Factor (VIF)

Variance inflation factor statistic is utilized to assess multi-collinearity in the indicators (Fornell & Larcker, 1981). According to (Hair et al., 2017), multi-collinearity is not a serious issue if the value for VIF is below 0.5. As reported in table 3.5, the VIF values for the indicators reveal that the VIF for each of the indicators is below the recommended threshold.

Table 3.5
Variance inflation factor (VIF)

	VIF
Perceived ease of Use 1	1.46
Perceived ease of Use 2	2.617
Perceived ease of Use 3	2.074
Perceived ease of Use 4	2.62
Perceived ease of Use 5	3.053
Perceived Risk to Customer Acceptance 1	2.162
Perceived Risk to Customer Acceptance 2	3.089
Perceived Risk to Customer Acceptance 3	2.847
Perceived Risk to Customer Acceptance 4	3.399
Perceived Risk to Customer Acceptance 5	1.626
Perceived Risk to Customer Acceptance 6	2.327
Usage3	1.433
Usage4	1.608
Usage5	1.906

The estimation elements have been extracted from existing elements in previous studies and further modified to fit the analysis. For all scales, 5-point Likert response designs were used (i.e. 1: strongly disagree and 5: strongly agree). Moreover, two questions have been used actually to account for the expected relationship checks. The first question is about the usage of the contactless application by the customers, using five questions. The perceived health risk was estimated using four elements from the existing analysis (Wang & Hung, 2015). In addition, to measure the expectation of contactless hotel applications, seven questions have been asked in light of existing cases (Chan & Tung, 2019). Likewise, the structural model's validity requires examining the coefficient of determinations (R^2) and path coefficients (Yang et al., 2021).

The Structural Model (SEM)

Once the measurement model results are satisfactory, the next step in evaluating the PLS-SEM results is to assess the structural model, which entails testing all hypotheses to determine the effect of exogenous variables on endogenous variables in order to answer the research questions. The structural model has four main criteria used in the evaluation including and as reported in the findings of (Hair et al., 2014).

i) Estimation of path coefficient (β)
ii) Determination coefficient (R^2)
iii) Effect size (f^2)
iv) Prediction relevance (Q^2)

Table 3.6 reported that the first hypothesis (H_1) states that the customer usage contactless hotel application accepts the application. It is defined when the result shows that there is a significant positive (β = 0.603, t = 6.964, p-value = 0.000). But it does not support the moderating effect of perceived health risk towards the acceptance of customers using contactless hotel applications, as shown in Table 3.6 (β = -0.028, t = 0.64, p-value = 0.522). This shows that the β value has the significant impact between independent variable (IV) and dependent variable (DV). In the same way, it is seen that the higher the β value, the stronger the effect of IV on the DV.

Table 3.6
Path Coefficients(β), t-Statistics and the p-Value of SEM

	(β)	t Statistics	P Values	Hypothesis
CU ->PEU	0.603	6.964	0	Accepted
ME1 ->PEU	-0.028	0.64	0.523	Not Accepted

Note: Moderating Effect 1= ME1

Coefficient of Determination (R^2)

The coefficient of the determination *(R^2)* value indicates the amount of variance in a dependent variable that explained by the independent variable. In other words, the measurement model explains the proportion of variability in the data. This value should be high to explain the endogenous latent variable variance in a well manner and the R2 indicates how much the external construct adds to the endogenous construct's explanation. The numbers range from 0 to 1, with higher numbers denoting stronger explanatory power. Acceptable R2 values, on the other hand, vary depending on the setting of the study. Likewise, perceptions and intentions have a poor R2 in investigations of human attitudes, often less

than 50%. Even so, because these values are difficult to forecast, it is regarded as satisfactory (Hair et al., 2017). The result of the analysis reveals R^2 value of 0.600 for contactless usage. This show that a 60% variance in the contactless usage can be attributed to contactless application. Based on the recommended by Hair et al (2017) results indicated that model obtained acceptable R^2 statistic for contactless usage is substantial.

Table 3.7
Coefficient of Determination (R^2)

	R Square	R Square Adjusted
Perceived ease of Use	0.600	0.592

The Effect Size (f^2)

The effect size is the change in the R2 value when a certain exogenous is added or deleted from the model. Hence, the effect size is used to determine whether changes in an exogenous variable significantly impact endogenous variables. Small, medium, and large effect sizes are represented by values higher than 0.02, 0.15, and 0.35 as a rule of thumb. If the 2 numbers are less than 0.02, it means that the modifications had no effect (Cohen, 1988). Data presented in Table 3.8 shows that contactless usage has a large effect (0.533) on their acceptance in using contactless hotel applications. Perceived health risk has a medium effect in accepting the contactless hotel application. Whereas the moderating effect shows a small effect on the acceptance of contactless hotel application.

Table 3.8
The Effect Size (f^2)

	f^2	**Effect Size**
Perceived ease of Use	0.533	Large Effect
Moderating Effect 1	0.01	Small Effect
Perceived Risk to Customer Acceptance	0.052	Medium Effect

Predictive Relevance (Q^2)

Predictive relevance is a significant statistical parameter in management and social sciences studies. Therefore, calculating the Q^2 value is another way to assess the predicting accuracy of the PLS path model (Geisser, 1975). To infer that the PLS-path model has predictive validity, Q^2 values should be greater than zero (0) as a guideline (Chin, 1998). Statistical rule of thumb says that values greater than 0, 0.25, and 0.5 indicate that an exogenous construct has moderate, medium, or substantial prediction accuracy for a given endogenous construct respectively (Henseler et al., 2015). As shown in Table 3.9, Q2 shows the predictive relevance of the endogenous constructs. Similarly, Q2 value above than 0 shows that the model has predictive relevance where acceptance is 0.372.

Table 3.9
Q^2 Values -Predictive Relevance

Endogenous Construct	Q^2	Predictive Relevance
Perceived use of Use	0.372	Moderate

Standard Root Mean Squared Residual (SRMR)

It was found that standard for acceptable fit as standard root mean squared residual (SRMR) should be less than 0.10, that establish the SRMR for the hypothesis is 0.093, while the ideal value for NFI must be above 0.9 (Hair et al., 2017). These results demonstrate acceptable fit. According to Hair et al (2017) standard for acceptable fit, SRMR should be less than 0.10, that establishes the SRMR for the hypothesis is 0.093, while the ideal value for NFI must be above 0.9 where the result demonstrate acceptable fit as reported in Table 3.10.

Table 3.10
Model Fit SRMR

	Saturated Model
SRMR	0.091
NFI	0.90

Hypotheses Testing

Hypothesis is framed in order to check the proposed relationship between research frameworks. In the current study, the research framework includes one independent variable, one dependent variable, and one moderating variable. Likewise, PLS-SEM structural model (CI) was used to test the relationship among variables with statistical parameters as path coefficient (β), and significance level (p-value) derived from the 85 percent confidence intervals. Through the PLS-SEM test, both hypotheses are tested to assess the relationship of proposed frameworks.

Table 3.11
Bootstrapping

	Original Sample	Standard Deviation	T statistics	P Value
Usage -> Perceived ease of Use	0.603	0.089	6.964	0
Moderating Effect 1 -> Perceived Ease of Use	-0.028	0.044	0.64	0.523

H_1: There is a significant relationship between perceived usefulness and perceived ease of use.

Hypothesis H_1 assesses the perceived usefulness significantly impacts the perceived ease of use. The result revealed that perceived usefulness significantly impacts the perceived ease of use (β =0.603, t=6.964, $p < 0.001$). Hence, H_1 is significant and approved.

H_2: Perceived Risk to customer acceptance has a moderating effect on the relationship between perceived usefulness and perceived ease of use

Hypothesis H_2 assesses the customer perceived risk has a moderating effect on the relationship between perceived usefulness and perceived ease of use. The result revealed that perceived health risk has insignificant effect on customers' acceptance (β =-0.028, t=0.64, $p > 0.001$). Hence, H_2 is not significant and there is no moderating effect of customer perceived health risk on the relationship between perceived usefulness and perceived ease of use and hence hypothesis is rejected.

Discussion

The current research delves deeply into the three facets of client approval (usefulness, acceptance, and perceived health risk) of the contactless hotel application. We also looked into how customers' perceptions of health risks affected their propensity to use the hotel's contactless app. A number of statistical studies were performed to shed light on the investigation of the aforementioned connections and influences. Pearson product-moment correlations were calculated to look at how the variables in the study were connected to one another and in what ways. Likewise, the two primary hypotheses were identified and explored using Smart-PLS (H1 and H2). As a result of the Covid-19 outbreak, hotels had to quickly implement new procedures to reassure their patrons that they were safe. In this post-pandemic period, the friendship industry must adopt the innovations seen in the hotel industry. There's no doubt that the majority of businesses suffered losses throughout the pandemic. But if a hotel chain provides hotel intermediate and creative management meetings, problems like high expenses, layoffs, and inconvenient meetings can arise.

There has been great progress in attracting hotel guests even after the pandemic, as evidenced by the survey results, despite the fact that the adoption of new development and technology applications will come at an additional expense for hoteliers. As a result, you'll need to think about the advance interest in the bigger picture. The findings of the study show that significant progress can be made in lowering the perceived health hazards without resorting to hotel innovations that result in social isolation. Hotels may concentrate on cashing checks when investing in costly technological innovations like robotic upgrades thanks to this system (Lukanova & Ilieva, 2019). Furthermore, hotel owners should make sure that the introduction of mechanization and modern mechanics does not lead to the actual removal of human jobs, but rather to the development of new ones in various places to counteract the hotel's negative economic impact (Alonso et al., 2020). In addition to assisting hotels in keeping up with the quality of support provided by employees in new, more creative roles, these methods will also encourage such personnel to stay with the establishment. Lastly, this research proves that guests' perceptions of health risks during dynamic processes can be mitigated by providing them with accurate information about the hotel's risk mitigation strategies (Meents & Verhagen, 2018). Thus, it is important for hotels to cooperate with one another.

Conclusion

Therefore, hotels should take the initiative to provide their guests with up-to-date information by developing stronger channels of contact (Berezan et al., 2016). Therefore, it is clear that the most crucial risk mitigation technique for hotel customers during the pandemic is to follow the hotel's advice. This was followed by the normally low-scoring activity of reading publications and pre-managing data before the pandemic. In addition, the results of the current study corroborate those of the previous study, suggesting that hotels should give optimal and accurate data and enhance the preparedness of frontline workers. Consumers, on the other hand, are less picky about their purchasing experiences. Furthermore, it was discovered that, as a result of people's increasingly isolated social lives and nontraditional vacation habits, guests' perception of danger is not mitigated by their familiarity with hotel amenities and services. Customers' anxiety about contracting an illness is likely to increase as a result of these operations. Because of this, hotel owners and operators are urged to alter their marketing strategies and provide more "contactless" services in order to protect their

clients from the potential adverse effects of Covid-19. The study found that customers' risk perception is influenced by segment characteristics due to the risk or fear of the pandemic. As a result, hotels must employ varied strategies for development and presentation in order to cater to their various clientele. Hotel chains that want to succeed must adapt to the changing times by capitalizing on emerging markets worldwide. Also, this research may help in designing more effective displays for pandemic relief. Financial services are another sector that has been impacted by technological advancements, allowing businesses to meet the needs of their clientele better. The application of modern technology can enhance service quality. Customers can save time and effort by doing financial transactions online. There are two challenges for every invention, as stated by Bongaerts et al. (2017): the first is to develop it, which is all about engineering and technology, and the second is to market it, which is all about the mind and design that forms the customer perspective. The "disruption map" combines these two perspectives to effectively visualise what is technically possible and commercially viable. This research was conducted to answer the question of whether consumers would adopt emerging technologies, with a focus on the viability of contactless applications that eliminate the need for human interaction.

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