CONDITIONS THAT INFLUENCE USERS TO SHARE MEDICAL INFORMATION VIA CONSUMER APPLICATIONS. AN EVIDENCE FROM ISRAEL HEALTHCARE SECTOR

T.Katz [1], D.Grimaldi [2*]

[1]Ramon Llull University – tomer.katz@students.salle.url.edu
[2]La Salle Faculty, Ramon Llull University – didier.grimaldi@salle.url.edu
Department of Management, Ramon Llull University, 08022 Barcelona Spain

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ABSTRACT:

Data-driven technologies are being greatly adopted in healthcare in order to create a better ecosystem of health for citizens in the development of smart cities. As we develop smart devices and services, there are growing concerns in the population's perception around privacy concerns in using these devices and services, and the necessity to share their medical sensitive information is often perceived as a holdback. The following study goal is to develop a model to better understand the conditions affecting privacy concerns in medical devices and services. Using primary research to test the suggested model using secondary research methods, and data analysis tools using python program with pandas library and ANOVA statistics. The solution proposed can offer a methodology for building health services in smarter and more connected cities.

1. INTRODUCTION

Smart City pursues the goal to improve citizens' life through the use of technology (Grimaldi and Fernandez, 2017). Emerging technologies like Big Data, Artificial Intelligence, and the Internet of Things have started to show their benefit, lowering costs and improving urban operations efficiency (Deloitte 2015).

The potential value of smart cities both economically and socially is very ambitious, and companies such as IBM and Intel, are launching programs to consolidate their guidance in this sector, and they have recognized smart health to be among the most important fields that will play key roles in making a smart city (Pramanik et al., 2017).

Applied for medical purposes, they can improve the quality of our lives (Grimaldi, Collins, and Acosta, 2021). Indeed, by bringing data-driven technology to healthcare, we can learn more about patients in different ways, provide necessary treatment proactively and enable the delivery of better-personalized care. There is a large growing demand for healthcare products driven by data-driven technologies. Often developed by startups, the global digital health funding has been constantly breaking records in the last 3 years with current funding of 57.2B, and mostly aiming towards applications for mental health startups and telehealth (Heather Landi, 2022).

Big data developments for solutions within the urban and social smart city umbrella are focal for the adaptation of smart devices and medical apps in the everyday life of its users. Those data-driven devices can track and gather information about us with little to no intervention by the prospect. In order for this synergy to work at its best, sensitive information about our medical records needs to be integrated within different suppliers within the public and the private sector (Zhang, D. et al., 2021).

Developing technological solutions are essential, but without considering adaptation willingness to those technology solutions, it often makes the solution itself useless (Grimaldi and Fernandez, 2018). On one hand, developing solutions for healthcare in smart cities using emerging technologies will indefinitely improve users' health products, drive down costs, and overall can save lives (Pramanik et al., 2017). But on the other hand, many of these technologies have been subject to skepticism around the world, with over 90 percent of global online users having at least one major concern about data privacy (Johnson, 2021).

* Corresponding author

A survey conducted from November to December 2019 suggested that 47 percent of the responders were worried about their personal information being exposed to a cyberattack, and another 40 percent of worldwide responders stated that they feel discomfort about sensitive information being sold to third parties and used without their consent (Johnson,2021).

Privacy concerns left unaddressed may restrict people from taking advantage of the full benefits of the service and make us more reluctant towards smart cities development. There is possibility of social unrest due to concerns that these devices will be used for monitoring and tracking individuals by government agencies or third-party companies (Al Ameen et al.,2012).

The research question that was accumulated following primary research is, What are the factors or conditions that motivate users to share their personal health information in digital services and consumer applications. Our manuscript has the objective to determine, classify and rank the conditions and external factors that influence people to share their health information and adopt the use of digital platforms and devices for medical purposes. In order to develop innovations in healthcare when designing services for smart cities using data-driven technologies, we must first comprehend that designing a suitable environment for the users to feel safe and trustworthy is essential from the embryonic stage.

This study is in line with the line of research pursued by (Jing, 2016), (Scott, S. D 2008) but this will constitute a country variable that will be examined in Israel, which has very little research data to be drawn from. This research is a step forward in the research applied in the domain of the conditions of technology used for medical purposes. Few studies have made an analysis but all of them are partial (Atchariyachanvanich et al.2017). Our results will permit us to define for the first time a comprehensive model, specific to digital platform solutions.

2. LITERATURE REVIEW

Concerns about privacy issues left undressed can cause major disruptions in the development of smart technologies within urban areas and can arise social conflicts which eventually make these technologies futile (Zhang, D. et al., 2021). As recent evidence, the extremely ambitious project by Sidewalk Labs, Google's subsidiary for urban planning and infrastructure, developed a plan to build "the world's first neighborhood built from the internet up".

Based in Toronto, the studio had planned to build a smart neighborhood that would thrive on data analysis from sensors, smart devices and cameras, and make use of all that data to track and increase life quality. The project raised many questions about the mass collection of data and was eventually shut down due to concerns of data harvesting, privacy risks, and an overall lack of transparency (Zhang, D. et al., 2021).

To develop a smart city, acknowledgment of an established smart health ecosystem is one of the most important factors of success (Pramanik et al., 2017). We know that privacy concerns left unaddressed is a downgrade of the full potential of the technology to attain value to its users, and might become futile in the process. US nationwide poll by Harris from 2006 revealed that one-quarter of the U.S adults have significant concerns about the use of their health information and 50 percent believe they have lost control over how their data is being used and sold to third-party companies for commercial purposes (Anderson, C. L et al. 2011). In the US, the healthcare industry had created a set of policies for regulations, their purpose intended to protect health information sensitive data.

Policies such as the health insurance and portability and accountability act (HIPAA), and the health information technology for economic and clinical health act (HITECH) were developed to improve health systems and ensure all healthcare organizations secure their health information (Hathaliya, J. J. et al, 2020). These policies are important to secure some part of the problem, but they do not guarantee that patients' data will be protected against security attacks, especially when we are shifting towards a more cloud-based flow of information.

In 2018, the European Union initiated the beginning of the mandated privacy law policy (GDPR), which applies to all organizations that collect and process the personal information of EU citizens within or outside of the EU borders. This implies that all companies that wish to collect information on EU citizens need to declare and state that they are fulfilling the GDPR privacy policies and compliance levels in their privacy policies. To bring those policies to the test, a group of researchers from The University of Texas at Austin, decided to examine 550 different privacy policies which were divided into pre and post the GDPR years (Zaeem, R., et al. N 2021).

The result shows an overall increase in the data protection guidelines meaning that post GDPR, users experienced more control over their data overall, The researchers also found that post GDPR, levels of deleting or editing information had surprisingly decreased, and users are in fact righteous when it comes to the decision to terminate their information in the service. (Zaeem, R., et al. N 2021). Other areas that were found to be blurred, missing, or incomplete were the clear mentioning of encryption of data while at rest, notification of supervisory authority in case of a data breach, and clear agreement to require informative accord (Zaeem, R., et al. N 2021).

This discrepancy is unveiling that more work is necessary for the field of privacy regulation and that the rapid evolution of web2 and now the beginning of web3, shows us that regulation in this field has to be an adaptive and constant state of emulation to ensure gaps are not formed. The access to personal information and the ability to analyze it in order to optimize personal experiences, drive sales, and increase value has been shaping the global new economy (Isaak, J., & Hanna, M. J. (2018).

3. METHODOLOGY

This research is set to test what independent variables can we apply in order to achieve trustworthiness and willingness to share sensitive information. A model will develop based on 5 independent variables that are tested empirically to validate and measure their impact on data privacy concerns and what conditions should we apply in designing those data-driven technologies to foster a safer environment for users.

The selected independent variables were in line with similar research pursued by (Jing, 2016), (Scott, S. D 2008), and is taking into consideration parts of Everett Rogers, diffusion of innovations theory. This theory will help understand how ideas and innovations are adopted, and it is an essential theory to consider when developing new innovations in every industry. In the healthcare context, this theory will help us understand the importance of innovation adaptation variables in managing privacy concerns in digital health services.

Our methodology is based on an empirical research and deductive method. 6 constructs are defined and a model is developed which contains 5 different independent constructs and one dependent one. We test separately if each of these 5 constructs has a potential effect on the adoption of technology and innovation while designing digital solutions for healthcare. The model will be tested through a Bayesian statistic-based survey which ensures all the collected data are exogenous, and will be analyzed with data analysis tools such as python programming using the pandas library and ANOVA statistics. The information been recorded does not require an ethical approval since there was no collection of personal data from the responders.

3.1. Transparency

Transparency is the ability of the user to receive information about the service objectives, usage and processes of their data in the platform. It is the option of the user to learn how their data is being used and which stakeholders have access to this data. Perhaps the most discussed factor today, transparency holds a big role in how big companies interact with their users.

3.2. Engagement

Engagement is referred to as the level of involvement and dedication the service is able to evoke in its users. Engagement is highly associated with feelings. The ability of the service to keep its users active and explorative of the different possibilities the service has to offer.

3.3. Personalization

Personalization is the ability of the service to tailor the experience and the products being used on the service directly and specifically to its user needs.

3.4. Relative Advantage (RA)

Relative advantage is the degree to which an innovation is perceived as being better than the idea it supersedes (Rogers EM,1995). This enables us to understand if users will replace their exciting solution with the new service.

3.5. Complexity

The range of complexity being perceived by the users will determine their willingness to participate in the service (Rogers EM,1995). The diffusion of innovation theory suggests that complexed new solution that are not easy to operate will have less chances of being adopted.

3.6. Service – Depended Variable

Service is the representation of our dependent variable which relates to the basic characteristics of the service and was tested in the last part of the survey.

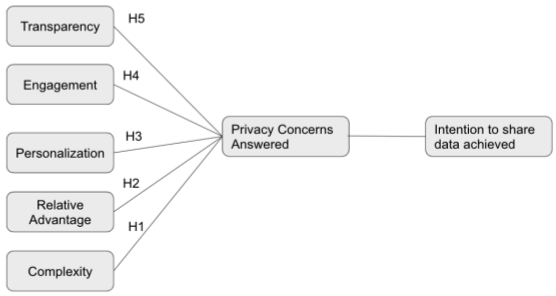

Figure 1. The suggested model

4. KEY FINDINGS

The survey collected 119 responses and was analyzed and measured in four ways. First, the Demographic information and the technology readiness of the responders were analyzed. Second, we analyzed each construct variable set of statements, each statement was scored and measured. This helped us to understand which statements were more important than others in terms of development tools considering the suggested construct, and an average score helped us to detriment the importance of each construct in relation to privacy concerns.

The third part of the analysis was to examine the correlation between different constructs using a matrix table score, this helped us to understand whether one construct can or can not exist in the absence of another. The fourth and last part of the survey was an ANOVA test, whose purpose is to examine if there is any comparison between different sets of group ages.

The age distribution is stated in Table2. We can see that the large majority of the responders were young adults, ranging from 18 to 34. In Table3 you will find the gender distribution, which indicates there were more than double male responders as females. Table4 states the level of technology readiness by classifying the level of computer use on average every week, and it indicates that most of the responders were using computer devices every day, therefore the level of technology readiness for the responders in this survey was higher than expected.

Each variable set of statements was tested in standalone and was given an average score of mean and standard deviation (std), which you can find in Table4. The full analysis will be presented in Table5.

Looking at each variable on its own, we are able to see that some of the statements received a higher mean than others, and std was respectably distributed. Looking at the mean score from 1 being the lowest to 5 being the highest, the statement in Transparency related to consent from the users every time data has to be shared, received the highest score among the set of statements (4.3), and in relation to a statement about receiving an update each time user data is shared, which received the lowest (3.4) both in mean and in std. This can indicate that users' consent to sharing their information is prominent, but they do not want to receive updates each time their data is being shared with other companies.

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Examining Relative advantage, almost all the statements received a mean score of 4.0, and the highest recorded std (0.9) was in a statement related to the ability to get access to experts around the world.

Regarding Engagement, the statements about the ability to provide feedback on the digital health service had the highest mean (3.8) while the statement surrounding the ability to share user progress with other users appeared least desired (2.7 mean). This can suggest that users value their ability to be heard and provide feedback on medical devices, but they are less keen to share and communicate with other users on their medical information.

In Table4, you will find an average of each set of statements related to their variable, this shows us that Personalization and Relative Advantage achieved the highest scores of 4.1 and 4.0 accordingly, and also the lowest STD recorded, meaning that all answers were similar to each other, and recipients largely agreed on the important facts on these constructs.

Transparency had a high STD following a high mean (3.9), this states that responders were also divided in their answers despite largely identifying the importance of the construct. Complexity recorded the lowest mean of 3.1 despite the assumption that it is considered a highly valuable construct to take into consideration. On a scale of 1-5, all these constructs achieved high scores above 50 percent, where the lowest one is 3.0.

Complexity was assumed to be ranked as high as relative advantage, as for the high importance it perceived to have. This has proved to be wrong as Complexity places the lowest mean average score in relation to all examined constructs.

The third part of the analysis was to aggregate each construct and test the correlation between the different constructs that were tested, to examine whether they are dependent on each other (Table 6).The distribution of the score was from 0-to 1, with 0 being no correlation at all and 1 with high correlation, results over 0.30 were considered correlated. In table 6, you will find the correlation matrix result.

The results have shown the highest correlation between Relative Advantage and Personalization (0.42), followed by Personalization and Transparency (0.37), and after Personalization and Service (0.31). A score below 0.30 was not considered correlated. Therefore we can indicate that Personalization is highly correlated to Relative Advantage, Transparency, and Service, but Relative Advantage and Transparency are not correlated (0.22), nor are Service and Relative Advantage (0.26) or Service and Transparency (0.065).

This tells us that Personalization is the most reliable construct, and including this construct in the digital health service developed will require the consideration of Relative Advantage, Transparency, and Service. On the other side, Transparency and Engagement showed little to no correlation (0.013), Transparency and Complexity (0.062), and Transparency and Service (0.065).

In the fourth and last part of the analysis, we applied ANOVA testing method to find out if there was any difference in responses between the different groups of ages examined, we found that statistically wise there was no difference in the answers by those groups of ages. As assumed, different groups of ages think differently in adaptation of technology and have different world views. This had been proved to be wrong in this survey.

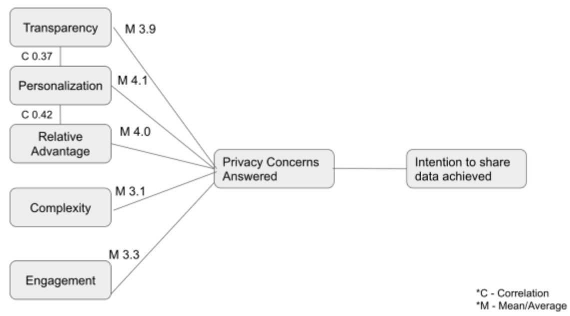

Figure 2. Results For Structural Model Of Privacy Concerns

5. DISCUSSION

In addition to (Jing, 2016) research, we have also identified that Personalization has a direct link and it is dependent on constructs such as Relative Advantage and Transparency. Relative Advantage has been examined and proved to be contributing to influence adaptation to medical devices in (Scott, S. D 2008) work, but has not proved to be a direct link to Personalization, and (Scott, S. D 2008) work did not suggest that it is also mitigating privacy concerns.

Therefore, our work has proved 2 major points that was not covered in both works by (Jing, 2016), (Scott, S. D 2008), one being that there is correlation between Personalization and Relative Advantage, and the other is that Relative Advantage is mitigating privacy concerns from user perspective. Users' privacy concerns will mitigate when applying Relative Advantage, but in order for that to fulfill its full potential, Personalization will need to be included.

In relation to complexity examined by (Scott, S. D 2008), where it was found correlated to compatibility, in our research we have not identified any correlation towards all the constructs measured in our research. Overall Complexity received the lowest score from all constructs (3.1) as opposed to the assumption before examining the results. Relative Advantage and Complexity were applied from the diffusion of innovations theory (Rogers EM,1995), associating both constructs as influencers on innovation adaptation.

Engagement was not examined in both (Jing, 2016), (Scott, S. D 2008). It was assumed to have a big impact on the social aspect of using digital tools, and it is a variable that is highly researched and perpetually considered in the technology industry as a driving force in users participation and overall satisfaction with the service (Lo Presti.et al,2019). In our analysis we have found that Engagement was the second least important construct in our analysis (3.3), and was not found to be correlated to any other construct we examined.

This can indicate that Engagement has little effect on answering privacy concerns in medical devices, and users are not perceiving this to be an important factor in the digital health service. Personalization has shown a positive effect on perceived benefits covered by (Atchariyachanvanich et al.2017), which approved their hypothesis that personalized service is positively related to perceived benefits in disclosure of medical data via mobile apps.

We can support this hypothesis by our research and suggest that both Personalization and Perceived Benefit are correlated constructs, and that they are positively related to answering privacy concerns. our research together with (Atchariyachanvanich et al.2017) can raise the suggestion that privacy concerns are proven to be answered when applying Personalization and Perceived Benefit processes within the design of the digital health service. That leads us to assume that with technology based products such as IoT and AI algorithms, we can produce better adjustable services that develop better Personalization and Perceived Benefit processes.

With the help of designing a smart city infrastructure, we can develop under the umbrella of emerging technologies that are set to support a smart city, a variety of different solutions and products tailored to different groups of the society. Considering the model developed and proved in this work will help us make sure these technologies are highly adopted by the population, and will not cause a major dissonance between technology and society. (Zhang D et al**,** 2021)

In (Liu C.-F et al ,2013) work, they have also tested a construct called Perceived Usefulness, which according to their analysis, was found to be the most significant factor in adaptation of PHR web based systems. According to the nature of their concept, Perceived Usefulness determines the level of the patience to perceive the digital health service as useful.

This is suggested to be compared to Relative Advantage, as the initial purpose of both constructs can be the same. Nevertheless, we do not have any evidence that these constructs Relative Advantage and Perceived Usefulness are indeed correlated and can also be addressed as similar. Further investigation for the research can be expend in order to reach concrete evidence, but this paper suggest that as Relative Advantage can be seem correlated to Perceived Usefulness, therefore we can raise the assumption that Perceived Usefulness has a positive effect in regards to users willingness to share their private data. This has been proven in the previous work of (Liu, C.-F., et al,2013), but can not share insights on today's discussed technologies and privacy concerns dilemmas due to its releasing year.

As we design and build cities to be smarter to to improve citizens' life using technology (Grimaldi and Fernandez, 2017), we must alleviate healthcare services as one of the pilers of improving the quality of life with technology. Smart cities salience of using top edge emerging technologies will provide solutions to various problems we face today, and can greatly increase our interaction with health services, making them easier to use while driving down costs and save us time. In this research we proved that when focusing on transparent, personal and more efficient services can greatly increase user adaptation in the process of making a city smarter and more connected.

As we build technologies in healthcare that will improve citizens life in a smart city, we want to keep in mind that the end user can be reluctant to use such services if we are not carful in designing services that answer their needs in the modern area of digitalization. The world is becoming more centric around digital solutions which brings great number of values but also tackles new problems such as privacy concerns examined in this paper. If we want to design the cities of tomorrow without reaching futile results, we need to focus not only on the value these technologies provide, but also of the challenges.

6. CONCLUSION

Our research sole focus was in Israel and gathered 119 responders. There is more work to be done in better understating perception regarding privacy issues, and this can be done in expanding the number of participants that are in different levels of technology readiness. The majority of the responders in our survey identified a high level of technology readiness. A larger number of participants will help us to understand different levels of users in different technology knowledge levels, as medical devices are designed to be inclusive.

Another suggestion to improve demographics is to include more female participants, which is important to understand and examine both gender opinions towards privacy concerns, a suggestion to future research to be done. The last suggestion in demographics is to include more levels of older groups of ages in future research. This is important to identify group ages statistics and make comparison of the data between different sets of ages, as opposed to our ANOVA test which showed no difference in answers between all sets of ages. This research can be applied and expanded to other parts in Europe and the Middle East, to compare analysis and identify patterns that can be solved and addressed.

This study is an important first step towards understanding privacy issues in the Middle East, and overall understanding of privacy concerns while emerging technologies entering traditional industries such as healthcare. With promise of making traditional industries more smart and efficient in the development of smart city infrastructure, it is prominent to take into consideration the growing concerns for privacy of the sensitive information of the users, and making sure participants of these digital health service received the compositing value in exchange of revealing and sharing their information between the private and the public sector.

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APPENDIX

Table 1. Age distribution (survey)

Under 18	28
18-24	46
25-34	28
35-44	12
45-54	3
55-64	2
Over 64	0

Table 2. Gender distribution (survey)

Male	87
Female	32

Table 3. Technology readiness levels (survey)

use computer every day	102
rarely use it	3
few times a week	13
not at all	1

Table 4. Average score of each standalone variable

	Mean	STD
Transparency	3.9	1.3
Engagement	3.3	1.0
Personalization	4.1	0.8
Relative Advantage	4.0	0.9
Complexity	3.1	1.1
Service	3.7	1.0

Table 5. Full standalone variable analysis

	TR:From_me	TR:Third_party	TR:An_update	EN:Option	EN:My_progress
count	119	119	119	119	119
mean	3.94958	4.302521	3.495798	3.563025	2.798319
std	1.213265	1.232021	1.419441	0.996933	0.970583
min	1	1	1	1	1
25%	3.5	4	2	3	2
50%	4	5	4	4	3
75%	5	5	5	4	3
max	5	5	5	5	5

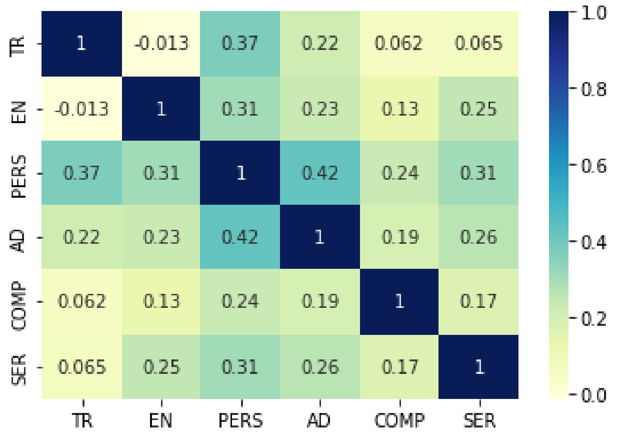
	EN:Feedback	EN:digital links	PERS:tailored	PERS:notifications
count	119	119	119	119
mean	3.857143	3.142857	4.310924	3.941176
std	0.976727	0.876102	0.698035	0.8366
min	1	1	2	1
25%	3	3	4	4
50%	4	3	4	4
75%	5	4	5	4
max	5	5	5	5

	PERS:learn	AD:Physically	AD:24x7	AD:Experts	COMP:1-login
count	119	119	119	119	119
mean	4.285714	4.084034	4.134454	3.890756	3.193277
std	0.738102	0.878942	0.891812	0.945909	1.209267
min	1	2	1	2	1
25%	4	3	4	3	2
50%	4	4	4	4	3
75%	5	5	5	5	4
max	5	5	5	5	5

	COMP:fitness	COMP:every_time	SER:multi-platform	SER:integration
count	119	119	119	119
mean	2.722689	3.420168	4.563025	3.07563
std	0.929045	1.061625	0.632973	1.215435
min	1	1	2	1
25%	2	3	4	2
50%	3	4	5	3
75%	3	4	5	4
max	5	5	5	5

	SER:free	SER:government
count	119	119
mean	3.932773	3.361345
std	1.047443	1.117891
min	1	1
25%	3	3
50%	4	4
75%	5	4
max	5	5

Table 6. Constructs Correlation Matrix



Survey reference - https://forms.gle/DL99qGXdsbcHfvFBA

<u>Transcript of the statements questioned in the Survey (Translated from English to Hebrew) Including a link to the survey page:</u>

- Gender
  Male/Woman
- Age
  Under 18
  18-24
  25-34
  35-44
  45-54
  55-65
  Over 64

- How often do you use a computer during the week
  Not at all
  Rarely use it
  Few times a week
  Use computer every day

I will use this digital service in the following condition:

- I know which medical data is collected from me
- The service need to ask my permission every time he wants to share my information with third party commercial companies
- I get an update every time my information is being shared with a commercial third party company
- I have an option to ask other users about the service
- I have the option to share my progress in the service and comment on other progress
- I can leave a review and a feedback on the service
- I have an option to share this service with other friends using digital links
- I will receive customized service tailored to my needs
- I get notifications on new medical treatments for my situation
- I can learn more about my medical situation
- It allows me to go less physically to the doctor
- It allows me to access support 24/7
- It allows me to get access to experts all over the world
- If i need more then 1 login for my account
- If i can't have my data shared on other fitness apps that i use
- If i need to verify information about my health every time i use the service
- This digital platform needs to be multi platform ios android etc
- It is important that i have integration with other relatable apps that i use
- It is important that this service should be free
- It is important that this information has access to my government information such as id, social security etc