

Exploring The Influence of Nudges in User Interface Design on Viewer Engagement and Satisfaction: A Study of Netflix and Amazon Prime Among College Going Students in Kerala Using MARS (Mobile App Rating Scale)

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How to cite this article: Nidhin Johny, Jitha G. Nair, Geo Jos Fernandez, Indu George, Jithin Benedict, Mahalakshmi Sankar, Manju Das S. K. (2024). Exploring The Influence Of Nudges In User Interface Design On Viewer Engagement And Satisfaction: A Study Of Netflix And Amazon Prime Among College Going Students In Kerala Using MARS (Mobile App Rating Scale). *Library Progress International*, 11567-11578,

Abstract

Netflix and Amazon Prime have established their dominance in the over-the-top streaming application business. They have constantly innovated and remained relevant even when people were skeptical about their survival post the pandemic. A large number of subscribers are students who have found a platform which streams content based on their choice rather than dishing out what the service providers in the traditional over-the-air, cable, or satellite-based services were offering. With the advent of cheap internet plans more and more subscribers found these apps very easy to use and a rampant adoption spree happened when these streaming platforms created user friendly and attractive mobile phone-based applications. A lot of these intuitive apps are created keeping in mind some Nudges that make these applications more engaging. This article will try to shed some light on the role of nudges embedded in the User Interface Design of OTT mobile apps and their impact on Viewer Engagement and Satisfaction.

I. Introduction

Background and rationale

Nudges have taken the world by storm. This concept was introduced by Richard Thaler and Cass Sunstein in their book *Nudge: Improving Decisions about health, wealth and happiness* (Thaler & Sunstein, 2009). The use of nudges was first advocated to help people understand the role of behavior in decision making and how nudges can be used to influence the way people decide. Nudges in a nutshell do not forbid you from opting for something that you wanted but would guide the subject towards a preferred option desired by the nudge designer (Lamprell et al., 2021). Nudges have been extensively used by governments and policy makers to influence how the common populace thinks and it has been found to be effective in certain contexts (Einfeld, 2019). This gave birth to the whole concept of libertarian paternalism where autonomy in decision making of a person is retained but the nudge designer guides the subject to make a decision that the designer thinks is best for the subject (Barton & Grüne-Yanoff, 2015).

Video Streaming Apps are mobile applications that help users to watch video-based content online by registering with the platform and then further proceed to create playlists and watched curated content on app (Chithra et al., 2022). A lot of people subject to the availability of the internet have switched over to these video streaming platforms (Kaur & Ashfaq, 2023) and this has caused an explosion in the quantum of content that has been created exclusively for these platforms. There are several factors that keep users hooked to these platforms but an attempt has been made in this study to better understand which factors in the *Mobile Application User Interface* are influencing users more and how they are different in Netflix and Amazon Prime.

Significance of studying nudges in user interface design for viewer engagement and satisfaction

As the usage of these video streaming platforms increases exponentially it is vital to understand the concept of *User Interface Design*. Many authors have long considered the user interface of the application a central component in the

adoption of the aforementioned apps (Oppermann, 2002). The user interface in the app helps the users to interact with the application and complete the desired tasks with considerable ease (Paap, 2001). This brings the design of the user interface to the forefront as a good design enhances the user experience (UX) and a bad one may force the user to stop using the app altogether. With high competition among the service providers, it would be imperative for the designers to create a user interface that increases viewer engagement and satisfaction. This is where Digital Nudges come into the picture (Weinmann et al., 2015). These nudges are cleverly crafted and included in the user interface so that they influence how users interact with the application and how they consume the content.

Research objectives and questions

Most User Interface design elements incorporate *Nudges* in a subtle manner so that it is not visible to the user. This creates an impression that the decisions taken by the user are his own and are not influenced by any external factor such as a *covert nudge* (Lu et al., 2021).

The idea of using covert or overt nudges has been the subject of a long-standing debate among academicians (Felsen et al., 2013). This paper primarily focuses on the use of covert nudges which might not be easily identifiable by the user so the research questions are based on how users perceive the apps to function. However, several elements in the *Mobile App Rating Scale* can be used to measure how nudges may have an impact on user perception or *User Experience (UX)*. This paper tries to address the following questions:

Research Question 1:

How do some select nudges influence the User Experience (UX) gained from Video Streaming apps like Netflix and Amazon Prime?

Research Question 2:

Is there any difference in the way people perceive the User Experience gained from Video Streaming apps like Netflix and Amazon Prime?

The aforementioned research questions were used to formulate the following **Research Objectives**:

1. To examine the influence of select nudges, such as Ease of use and Feedback (Information quality subscale from MARS) on the User Experience (UX) derived from video streaming apps like Netflix and Amazon Prime
2. To examine and compare the perceptions of User Experience (UX) gained from video streaming apps like Netflix and Amazon Prime among users, with the goal of identifying any differences in user perceptions, preferences, and satisfaction levels between the two platforms

Hypothesis

H1: There is a positive relationship between Ease of Use and Engagement

H2: There is a positive relationship between Information Quality and Engagement

H3: There is a significant difference between User perception of User Experience gained from Netflix and Amazon Prime.

Overview of Netflix and Amazon Prime in Kerala

During the literature review conducted for this paper some studies have been identified that address the satisfaction level and the preference for a specific OTT platform in Kerala (Sujith & Sumathy, 2021). The use of OTT platforms like Netflix and Amazon Prime increased during the

Pandemic Period as people wanted to enjoy their favorite movies within the safety and comfort of their homes (Gupta & Singharia, 2021). The popularity of OTT Platforms has been a point of concern for traditional movie theater exhibitors as a large chunk of their target audience has now shifted to OTT platforms (Jha, 2024). This popularity has now resulted in the Government of Kerala launching its own OTT Platform named "C Space" (Bureau, 2024). The above information is a testament to the growing popularity of OTT Platforms in Kerala.

Introduction to MARS as a measurement tool

The Mobile App Rating Scale was initially developed to assess the quality of health-based apps (Stoyanov et al., 2015). This scale was meticulously developed with the help of several experts and was validated in several contexts (Terhorst et al., 2020) and across various geographical areas (Messner et al., 2020). The various metrics used in these scales can be used to measure the different elements to User Experience which are universally applicable in all apps. Subscales such as "Information Quality" and "Ease of Use" are elements that are used to measure App quality in other scales too (Hyzy et al., 2022).

II. Literature Review

Theoretical framework: Nudges in user interface design and their impact on user behavior

The process of using Nudges in a digital environment is known as Digital Nudging (Sobolev, 2021). These nudges are incorporated into the software as design elements so that the users may use the application in a desired pattern but at the same time does not forbid them to choose anything that they may desire. There have been several instances where the interface designers have encountered problems like choice overload for the user which might lead to indecisions from the

users as they have too many things to choose from (Jesse & Jannach, 2021). Such situations may call for user interfaces that include only that information which is pertinent to the task at hand and all other items are hidden or obscured. The human brain primarily functions in 2 modes which was aptly explained in the Dual Process Theory (Kahneman, 2003). According to *Kahneman*, Humans make fast decisions based on heuristics which are done by the automatic thinking process of the brain.

While using an app too much information would prove inimical to the fast-decision-making process mentioned above. In order to counter this problem, the user interface should be designed in a way that enables fast decision making. This would improve the user experience thereby having a profound impact on the user behavior as people would be inclined to use software that is easy to use and enables rapid completion of desired tasks (Schneider et al., 2018). Ease of use is another factor that promotes increased use of the app. The ease-of-use concept was derived from the *Simplification Nudge* which attempts to simplify the desired message so that the adoption rate of the idea is increased (John & Blume, 2018). Software interfaces are primarily designed to be as simple as possible if they intend to garner higher usage. This simplicity results in a higher ease of use which further has a positive impact on the user behavior.

Previous studies on nudges in user interface design and viewer engagement

Consumption patterns of users have changed overtime. Starting off in the initial years from consuming what was delivered to them by the traditional media channels to selecting what they want to consume according to their own needs and wants. This phenomenon has been clearly documented in the *Uses and Gratification Theory* (UGT) (Vinney, 2024). It says that users choose to consume content from a medium expecting a set of benefits from it (Menon, 2022). The internet-based content consumption has increased post the Reliance Jio market disruption caused to one the lowest data rates in the world (Sundaravel & Elangovan, 2020). Due to the aforementioned condition many users have realized that they can consume content according to their own needs.

Viewer engagement in the internet parlance would be to encourage the viewers to engage with the content for the maximum amount of time in different forms so that they use the application for the maximum amount of time. This would be the quality of user experience that the user of the app may derive from the various functionalities available in the app like curated playlists, notifications etc. (Lehmann et al., 2012). Many nudges like *social proofing* when they were included in the interface design proved to be effective. Techniques like encouraging people to earn incentives and display it so that others may also be lured to use the app more to earn those incentives have been studied in the past (Huang et al., 2021). Some studies have also recommended the use of *gamification elements* to increase user engagement. Gamifying several aspects of the interface leads to the user spending more time on the application thereby increasing user engagement (Cheng, 2020).

Another study emphasized the use of a *simplification nudge* to promote user engagement (Auf et al., 2021). Interfaces that are difficult to use do not entice users to spend more time for the completion of the desired tasks. People are more likely to get disinterested very soon and may even move away from the app in the search of easier options. This specific way of user disinterest has propelled the use of simplification nudges in mobile application software's. Easy to use software interfaces garner more users as a decreased level of complexity enables people to complete their desired tasks easily and efficiently. This in turn results in people returning to use the app more frequently thereby increasing user engagement. Most studies conducted on nudges in the user interface have found some impact of nudge interventions on user/viewer engagement.

Theoretical foundations of MARS and its application in evaluating user satisfaction with mobile apps

The rampant use of mobile phone apps due to their widespread adoption has propped up the question of whether all of these apps are equal in terms of quality of user experience. Every other day a new app for the same purpose is developed. The question is whether the new app is any better than the previous one. In order to address the aforementioned issues several mobile application rating systems were developed. However, there was a lack of a rating system that would assess the quality of a purpose built "Health App". This prompted a group of 12 researchers led by Stoyan Stoyanov of the Queensland University of technology to embark on a quest to develop a scale that can assess the quality of a mobile health application.

An extensive literature review was done using data from more than 25 different sources which helped them to list 372 different criteria. Using a broad list as a starting point they finally arrived at the 23 item Mobile App Rating Scale or MARS. This scale has 5 broad sub scales in which four of them are objective scales and the fifth one is a subjective scale. The first four scales are "Engagement", "Functionality", "Aesthetics" and "Information quality". The last subjective scale rates the overall satisfaction with the app. The study shortlisted 60 different mobile apps and then used a select 10 apps to pilot the rating scale that they had developed. This method and the scale given above can be easily used to measure the quality level of apps from other domains such as Netflix and Amazon Prime. Scales pertaining to criteria such as engagement, functionality, aesthetics and information quality can be easily used to assess the quality of the streaming apps. As mentioned above the MARS Scale was created using 372 different assessment parameters so it has a design that can be replicated to measure the apps target in the study.

Analysis of user interface elements and nudges in streaming platforms

A great User Interface results in a great user experience which in turn results in viewer engagement. Streaming platforms have realized the importance of viewer engagement as they depend on the users to come back as frequently as possible to consume curated content for as long as possible. Nudges are a popular choice for UI designers to incorporate in their apps as they tend to encourage users to stay on a little longer or to come back a little sooner to their platform. Designers carefully chose nudges as all nudges may not have the same impact on decision making ability of consumers. Most people are unaware of the presence of nudges in the user interface as these nudge elements hide in plain sight but may have a huge impact on how the users interact with the platform. All user interfaces have the same working principles but they might differ in terms of the design principles. The whole objective of a streaming platform is to make the users spend as much time in the application as possible and be happy with the experience simultaneously. The above-mentioned idea is easy to think about but a whole different ball game to implement because the attention span to human beings is now being pegged at 8 seconds in 2013 (Roy, 2024). Nudges can enable the designers to ensure the users spend more time on the platform without getting bored.

III. Nudges in User Interface Design of Netflix and Amazon Prime

Overview of nudges in the user interface design of Netflix and Amazon Prime

An average everyday user of Netflix or Amazon Prime would not suspect the profound impact of nudges in their content consumption choices. The User Interface of these streaming platforms are brimming with different sorts of nudges. One way of influencing the decision-making process is by recommending content and this is where the recommender systems come in. The algorithm tries to learn the consumption patterns of its users and recommends tailor made suggestions (Shuaibu & Ramaiah Yeluripati, 2023). However, many researchers have asked questions about the intention of these recommendations and its impact on human autonomy in decision making (Krook & Blockx, 2023).

The whole idea of nudges is not to forbid a user select an option but to guide them towards a desired objective as envisioned by the choice architect. Choice architecture always has a goal and its inclusion of nudges allow the designers to achieve the desired objective. Both Amazon Prime and Netflix employ nudges in their own way. The biggest problem that these platforms have to solve is the problem of indecision of its users to choose a content due to the humongous number of choices that they have in front of them. This problem has been defined as a paradox of choice where too many choices lead to confusion and in the end, people do not take one (Kinjo & Ebina, 2015). The streaming platforms try to counter this problem by resorting to tools like persuasive design or using nudges like social proofing (Veigas et al., 2023). A bit of personalization in terms of content recommendations can also nudge users to consume more content.

Evaluation of key nudge elements (e.g., notifications, recommendations, social proof)

One thing that should be understood is that Nudges are a group of finite tools that cannot be applied on the whole to solve any given problem. Understanding which nudge to use is a million-dollar question. This is where researchers have come up with a solution which not only understands which nudge to use but also when to use. It might be hard to believe “Contextual Nudges” are very popular in UI design nowadays. A contextual nudge is an overt nudge that pops up in front of the user of the UI when it is relevant as deemed by the designer (Chacko, 2022).

Some of the nudges that are used most often by the designers are based on the idea that people tend to be different in what they like to watch and they also look for approval from their peers. The first nudge mentioned here is used via *personalized recommendations* where the users are recommended content based on their previous watch history and the second one is *highlighting content popularity* by using elements like top most watched movies or content lists which reassures a user that the content that he/she is going to has been watched and loved by many so there is a high degree of possibility that the content might be good.

The nudges mentioned above are overt in nature i.e. the user can easily see these nudges but designers also take into consideration other factors such as Miller’s Law. This law states that the human brain can store up to 7 (plus or minus 2) items in his working memory (Miller, 1994). A highly complex interface may deter a user from interacting with it and thus it was proposed that to increase usage the interfaces should be easy to use. Making contextual messaging (contextual nudges) simple has been found to be effective in nudging taxpayers to pay up properly and promptly (John & Blume, 2018). This same principle has been used by streaming platforms to ensure that the users interact with the interface and the content in it as much as possible. *Simplification* as a nudge will go a long way in ensuring consumer retention (Chadimova, 2023).

A Comparison of nudge strategies between the two platforms

Although both Netflix and Amazon Prime serve the same purpose, they have adopted some strategies differently in catering to different challenges faced by them. This is especially evident in India as consumers, though initially craving for international content, have now increasingly started to seek India specific content as they tend to connect with it more. Any tactic adopted by one company can be easily copied and the next company also will seek to take advantage of the aforementioned tactic. Overtime companies have come to rely on very complex algorithms that have evolved to meet the rising challenges in the industry. With rising internet speeds in India streaming content is not a problem anymore for the users of these platforms. With similar pricing and content, it all boils down to the experience that the people get while they are on the app.

Both companies have focused on creating a unique user experience (UX) with the help of their intuitive User Interface (UI). The use of nudges in these platforms has enhanced their ability to interact with the users with the intention of consumption of more content and to ensure that they come back to the platform again and again. Although there are subtle differences in the way nudges are applied by these platforms the discussion in this paper will focus on a select few. The best example is the use of a *hyper personalized* approach adopted by these platforms in which content is provided on the basis of the watch history of the users. The algorithm understands the pattern of choices that the user regularly makes and then recommends content accordingly. This technique has been used by both platforms but Netflix seems to have an upper hand here in how they deploy their algorithm.

The next approach is the *use of notifications* as a nudge tool. Streaming platforms have realized that the users may not be online on their app 24 X 7, so in order to nudge them back certain timely reminders are needed like a well-timed notification. This prompts the user to have a look back at the app and just check for new arrivals or just some content that may be on their watchlist. Amazon Prime has a superb way of adopting an omnichannel communication system that includes messaging via notifications on the phone, emails and in app messaging.

As discussed before complexity in the usage of the apps deters newcomers and also encourages existing users to search for avenues that are more user friendly. Hence making their applications as simple to use as possible gives an added advantage over the other. *Simplification* as a nudge is very critical here as most platforms have realized that people prefer easy to use interfaces. Easy onboarding and easy navigation have made the experience at these platforms much better for its users. The Netflix application is very minimalistic thereby employing the simplification nudge. On the other hand, Amazon Prime application is more cluttered with icons and content.

IV. Methodology

A descriptive research design was adopted during the course of the study to ensure that the present state of affairs was depicted in the best manner possible. Such a design was necessitated by the fact that an accurate description was more important than arriving at various conclusions that may be erroneous in nature. Researchers conducted the study among graduate and postgraduate students in India. For collecting data, researchers sought support from a variety of departmental heads or faculty members. In order to increase data collection efficiency, eliminate human error, and reduce costs, online surveys were used since respondents were scattered all over India (De Beuckelaer & Lievens, 2009).

Based on an individual-based conceptual model, respondents can be operationalized individually. As a result, the data are cross-sectional and obtained from a single source. In order to minimize the likelihood of Common Method Bias, the study followed the procedures suggested by (Podsakoff et al., 2003). A statement explaining the study's purpose, nature, and confidentiality was provided at the beginning of the online survey form. Students were explained that there are no correct or incorrect answers, and that they should respond to the questions based on their own experiences. Also, the questions and statements were distributed randomly so that participants did not perceive any connection between them (Podsakoff et al., 2003). Approximately 456 students were randomly selected to participate in the data collection process.

Data was collected between March 2024 and May 2024. To increase response rates, a reminder mail was sent every 15 days. After the stipulated time, we received a total of 456 responses. Following a thorough analysis of the responses for missing data, a sample of 456 respondents was considered for further analysis. Out of 456 responses were received, of which 264 students are in the 16-20 age group and 192 students are in the 21-25 age group. In terms of gender composition, there were 160 males and 296 females. 58% of the 456 respondents were pursuing graduate degrees, while 42% were pursuing postgraduate degrees.

Other Tools Used:

Paired Sample T Test:

This test was conducted to analyze whether there were significant differences between the mean scores of the respondents when they were given questions on Netflix and Amazon Prime. A paired sample t test is a method which is employed to understand the differences in means between two related samples (Mishra et al., 2019) and this was found to be apt in this case as the set of respondents were the same and they were answering questions on two different applications (Netflix and Amazon Prime).

Correlation:

Ease of use of the app was correlated with Engagement to check whether ease of use correlated with engagement levels. A similar exercise was conducted to check whether information quality correlated with engagement levels. Correlation is a statistical tool that can be used to assess the relationship between two or more sets of data (Asuero et al., 2006). As the data was parametric in nature the Karl Pearson's Correlation coefficient was used (Blyth, 1994).

SEM to Analyze Suggested Relationships

Structural Equation Modeling was conducted to establish the hypothesized relationships between Engagement levels, Ease of Use and Information Quality. SEM was conducted using WarpPLS which is a well-established tool for variance-based and factor-based structural equation modeling (SEM) using the partial least squares and factor-based methods (Kock, 2022).

V. Findings and Discussions (Approx. 800 words)

Quantitative analysis results using MARS scores (300 words)

Table- 1

Scores	Engagement	Functionality	Aesthetics	Information	Mean
Netflix	3.32	3.52	3.76	3.64	3.56
Amazon Prime	3.13	3.49	3.57	3.57	3.44

MARS questionnaire contains two elements: One element that measures the quality aspects of the app like engagement, Functionality, Aesthetics and Information Quality. Another element here is the subjectivity score which is ignored in this study. On the aforementioned parameters it is very evident that NETFLIX has an upper hand in all quality aspects measured using the MARS questionnaire as seen in Table 1. Such results are consistent with the data derived from other studies which conducted user perception studies on different populations (Rahe et al., 2021). Overtime Netflix has maintained an edge in quality aspects over Amazon Prime.

Correlation Results

(a) Correlation (Netflix)

Table 2

Correlation Netflix	Ease Of Use	Information Quality
Engagement	0.658	0.775

(b) Correlation (Amazon Prime)

Table 3

Correlation Amazon Prime	Ease Of Use	Information Quality
Engagement	0.625	0.615

Hypothesis 1:

Correlations between Ease of use and Engagement are 0.658 and 0.625 seen in Table 2, for Netflix and Amazon prime which leads to the acceptance of Hypothesis 1. In this case for both Netflix and Amazon prime the ease-of-use nudge is closely related to the level of engagement derived from the app. Such results are consistent with other research results which have found an impact of ease of use on engagement levels of the app (McLean, 2018).

Hypothesis 2:

Correlations between Information quality and Engagement are 0.775 and 0.615 as seen in Table 3, for Netflix and Amazon prime which leads to the acceptance of Hypothesis 2. In this case for both Netflix and Amazon Prime the Information quality (Feedback) nudge is closely related to the level of engagement derived from the app. Previous research on the same idea has provided results which are in line with the results of this study. Good Information quality keeps the engagement levels high and the users happy at the same time (Ali et al., 2021).

Hypothesis 3:

Results of the Paired Sample t test

Table 4
Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	engage_n	3.3158	456	.96566	.04522
	engage_a	3.1298	456	.97259	.04555
Pair 2	function_n	3.5219	456	1.00360	.04700
	function_a	3.4868	456	.85603	.04009
Pair 3	aesthetics_n	3.7602	456	1.10367	.05168
	aesthetics_a	3.5673	456	.96222	.04506
Pair 4	info_n	3.6386	456	1.09372	.05122
	info_a	3.5719	456	.95282	.04462
Pair 5	ease_n	3.9518	456	.85477	.04003
	ease_a	3.8421	456	.69635	.03261
Pair 6	recom_n	3.8713	456	.93502	.04379
	recom_a	3.7778	456	.78405	.03672

In Table 4 it can be clearly seen that Engagement levels are higher in Netflix compared to Amazon Prime with a mean of 3.3158 ± 0.956 for the former and 3.1298 ± 0.9725 for the latter. On all other parameters like functionality, aesthetics, information quality, ease of use and recommendations the same pattern can be observed.

Table 5

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Engage (N) – Engage (A)	.18596	.40889	.01915	.14834	.22359	9.712	455	.000
Pair 2	Function (N) - Function (A)	.03509	.46749	.02189	.00793	.07811	1.603	455	.000
Pair 3	Aesthetics (N) – Aesthetics (A)	.19298	.57611	.02698	.13996	.24600	7.153	455	.000
Pair 4	Info (N) – Info (A)	.06667	.36619	.01715	.03297	.10037	3.888	455	.000
Pair 5	Ease (N) – Ease (A)	.10965	.43732	.02048	.06940	.14989	5.354	455	.000
Pair 6	Recommend (N) - Recommend (A)	.09357	.44968	.02106	.05218	.13495	4.443	455	.000

Results from the paired sample t test, shown in Table 5, also vindicate the belief there is a significant difference between how Netflix is perceived vis-à-vis Amazon Prime. Pairwise comparisons on the various parameters conducted using the paired sample t test have shown that difference between the mean scores is positive which means in this case that the first item in the pair (Netflix) has a higher score than the second item in the pair (Amazon Prime). *Hypothesis: 3* is accepted here as this difference between the two streaming apps is significant. Mean scores of all parameters measured using the MARS Questionnaire with respect to Netflix are higher than the mean scores of Amazon prime.

Model Fit Using SEM

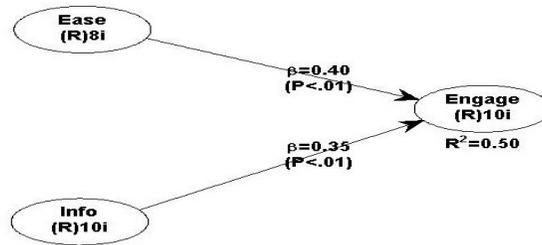


Figure: 1

Nudges like ease of use and information quality had a significant impact on engagement levels provided by the apps. Structural Equation Modeling done using WarpPLS is a clear indicator of the abovementioned statement. The model fit was evaluated using the Average Path Coefficient (APC), Average R² (ARS), and Average Variance Inflation Factor (AVIF). The APC (0.374, p < 0.001) and ARS (0.495, p < 0.001) values were both significant as seen in Figure 1. Multicollinearity was assessed with the Average block VIF (AVIF) and the full collinearity Variance Inflation Factor (AFVIF), with values below 2.425 indicating no significant multicollinearity problems. The overall goodness-of-fit (GoF) index of 0.563 confirmed the adequacy of the hypothesized model.

Combined loadings and cross-loadings of the model (Convergent Validity)

Table 6

	Ease	Info	Engage	Type (a)	SE	P value
N18	0.893	0.218	0.022	Reflect	0.042	<0.001
A18	0.838	0.186	-0.102	Reflect	0.042	<0.001
N19	0.89	0.095	-0.169	Reflect	0.042	<0.001
A19	0.88	0.124	-0.057	Reflect	0.042	<0.001
N20	0.761	-0.217	0.013	Reflect	0.042	<0.001
A20	0.645	0.229	0.054	Reflect	0.043	<0.001
N21	0.762	-0.327	0.169	Reflect	0.042	<0.001
A21	0.633	-0.437	0.147	Reflect	0.043	<0.001
N13	-0.089	0.848	0.102	Reflect	0.042	<0.001
A13	-0.222	0.842	0.1	Reflect	0.042	<0.001
N14	0.404	0.654	0.045	Reflect	0.043	<0.001
A14	0.104	0.599	0.087	Reflect	0.043	<0.001
N15	0.084	0.919	0.033	Reflect	0.041	<0.001
A15	0.061	0.887	-0.05	Reflect	0.042	<0.001
N16	0.098	0.863	-0.104	Reflect	0.042	<0.001
A16	-0.023	0.868	-0.14	Reflect	0.042	<0.001
N17	-0.05	0.894	-0.037	Reflect	0.042	<0.001
A17	-0.25	0.858	0.007	Reflect	0.042	<0.001
N1	0.261	-0.23	0.698	Reflect	0.043	<0.001
A1	0.088	-0.27	0.774	Reflect	0.042	<0.001
N2	0.264	-0.117	0.846	Reflect	0.042	<0.001
A2	-0.081	0.035	0.786	Reflect	0.042	<0.001
N3	0.214	-0.191	0.822	Reflect	0.042	<0.001
A3	0.079	-0.054	0.829	Reflect	0.042	<0.001
N4	-0.126	-0.017	0.687	Reflect	0.043	<0.001
A4	-0.144	0.04	0.739	Reflect	0.042	<0.001
N5	-0.339	0.408	0.771	Reflect	0.042	<0.001
A5	-0.254	0.4	0.775	Reflect	0.042	<0.001

Convergent validity of the model was checked using the indicator weights of each latent variable shown in Table 6. In order to accept the convergent validity all respective latent variables must be 0.5 or above. WarpPLS also provides effect sizes for the model. Interpretation of the effect sizes are based on the guidelines given by Jacob Cohen in his book Statistical Power Analysis for the Behavioral Sciences. According to him, Effect size indicates how much change the dependent variable can be explained by the independent variable (Cohen, 2013). The interpretation guideline is given below:

[Path coefficients are Low (0.02), moderate (0.15), or High (0.35)]

Table 7

Effect Sizes	Ease	Info
Engagement	0.264	0.231

It can be clearly seen in Table 7 that both Ease of Use and Information (Feedback) Nudges have a moderate impact on the level of engagement provided by the app which further validates the claim that nudges which are created properly will

have an impact on user behavior and more so in the case of a personally targeted mobile application where the entire attention of the user is on the application.

VI. Practical Implications

Most app creators have understood that an intuitive app design centered around the users will have a higher chance of adoption when compared to a complex less aesthetic looking app design. More and more app designers are looking to create apps that make onboarding and retaining an easy and less cumbersome process. Many new apps are struggling to survive as their User Interface designs run contrary to the basic tenets of User Interface (Picking et al., 2010). If a proper design revamp is conducted based on principles of user friendliness, feedback, aesthetic interface etc. the chances of having a successful app at hand would be comparatively higher.

In the race to create and dump new apps on the android and apple ecosystem many of them are doomed to fail from the start. The number of apps which are of poor quality is surprisingly high which is an indicator of how the aforementioned basic tenets of app design have been ignored over time (Inukollu et al., 2014). Keeping these simple tips during the app development phase will avoid a lot of course correction in the future and save a lot on unwanted testing and debugging expenses. Creating the best first impression during user onboarding may guarantee a long-term user who is happy with the product (Bhandari et al., 2015).

VII. Conclusion

An in-depth analysis of the data gives a lot of information as to how user interface designers can subtly include nudges in their apps to influence user behavior. A clear winner in this race right now is Netflix with a mean score of 3.56. But Amazon Prime is not very far behind and has a mean score of 3.44. Mobile App Rating Scale (MARS) was also found to be adept in judging user perceptions of the quality of the app and both applications fared well in the tests. A significant positive relationship was observed between ease of use and engagement, with path estimates showing $\beta=0.40$ ($p < 0.01$). Another significant positive relationship was observed between Information quality and engagement, with path estimates showing $\beta=0.35$ ($p < 0.01$). Therefore, to conclude it can be safely assumed that Netflix has an edge right now but as interface designs are evolving it may not be too far when Amazon Prime may catch up for good. Consumers can now sit and wait as these companies rush to create applications that are more and more intuitive and entertaining, which is surely a harbinger of great times ahead.

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