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Download or swipe left: The role of complexity, future-oriented emotions and feature overload

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ABSTRACT

With the intense competition in the mobile applications (apps) market, it is imperative for app providers to understand how visual stimuli from their apps can create a positive first impression and enhance the app download rates. In the present study, the mechanism through which visual complexity influences mobile app download intention is examined. Using a combination of convenience and snowball sampling, 218 participants were recruited to take part in a single-group post-test only quasi-experimental design. The findings of the study showed that visual complexity influences mobile app download intentions through the mediating role of two future-oriented emotions (i.e. hope and anticipated regret). Additionally, the study showed that the indirect effect of visual complexity on download intentions was moderated by feature overload with the importance of visual complexity significantly reducing as perceptions of feature overload increases. The proposed model explained 46% variance in the intentions to download a mobile app. The findings not only provide practical insights for mobile app developers and publishers but also theoretical insights on consumer decision making in the pre-use context of mobile apps.

1. Introduction

Over the past decade, globalization has been instrumental in intensifying the diffusion of technology across the world (International Monetary Fund, 2018). One technology that has been at the centre of globalization is smartphones as their increasing functional capabilities and ubiquity has transformed them to become vital productivity tools, and a mechanism for economic growth and delivering of the Sustainable Development Goals (Granryd, 2018; Hubler & Hartje, 2016). Smartphone diffusion amid globalization gave birth to the "App economy" which is a vital driver of job creation and economic growth (International Monetary Fund, 2019). It is therefore not surprising that the mobile application (apps) market has seen unprecedented growth over the years with various apps now being widely used for almost all daily activities (e.g. communication, entertainment, health and fitness, education, shopping etc.). This growth has resulted in enhanced competition in the mobile apps market as there are always many different apps with similar offering competing for user attention. At the start of 2020, there were over 2.2 million apps of the Apps Store and 2.8 million on the Google Play Store. With this high number, it is quite common that when searching for an app for a given function, a potential user is faced a multitude of options. For example, searching for a "time management app" or "puzzle block game" on the Google Play Store will yield more than 200 options for each category. With these many options, mobile app users are spoilt for choice and are thus very selective in the apps they decide to use. For example, users' first impression about the visual aesthetics of an app plays a significant role in determining whether or not they will decide to download and try the app (Bhandari et al., 2019). Thus, the decision to ignore some

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apps without testing them (swipe left) is relatively common in the context of mobile apps. Moreover, despite the billions of downloads recorded for mobile apps, the distribution is highly polarised with a very small percentage of apps accounting for a relatively large percentage of downloads (Burgers et al., 2016). Consequently, there is a need to understand why users might prefer to try some apps over others, as this can provide valuable insights for app developers and publishers (Bhandari et al., 2019; Lin & Chen, 2019; von Wangenheim et al., 2018).

The first decision users always make about an app is the decision on whether or not to download it (Bhandari et al., 2019), and only when they have downloaded an app will they then make a further second decision on whether to uninstall it or continue using it (Verkijika & De Wet, 2019). In the competitive apps landscape, users can only test a limited number of apps and as such, the decision to download an app is very crucial as it will then provide the opportunity for the user to fully assess it. In this critical pre-use context individuals often have to rely on visible aspects of the mobile app since they have not had a chance to interact with it. Such visible aspects are often available to the user as most mobile apps show their attributes and interfaces as adverts for the app. Consequently, researchers (Bhandari et al., 2019; Lin & Chen, 2019) have called for the need to examine the role that visual design elements play in influencing user download intentions. This is because unlike available metrics such as customer reviews, number of downloads and ratings, app developers can manipulate their visual design elements for their benefits.

Recent research in this domain has started to examine the role that visual design elements can play in shaping mobile app download decisions. For example, Bhandari et al. (2019) showed that user appraisal of classic and expressive aesthetics of a mobile app interface could significantly determine whether or not a user will download a given mobile app. Similarly, Lin and Chen (2019) showed that the visual design of app icons could significantly influence app download decisions. While these findings provide novel insights and set the stage for further dialogue in this domain, these studies only covered a limited number of visual design cues that could be vital in the pre-use context of mobile apps. As such, there is a need to consider and better understand the role that other visual design cues in the pre-use context could play since once size does not fit all in the mobile app selection process as different users might look for different visual design cues that resonate with them (Bhandari et al., 2019; Lin & Chen, 2019).

One possible visual design cue that has the potential to shape user decisions in the pre-use context of mobile apps is visual complexity. Visual complexity refers to the overall visual richness of an interface. Research suggests that individuals often weight pre-use decisions on visual complexity even to the extent that they might end up choosing overly complexity systems (Eytam et al., 2017). However little is known about the mechanisms through which visual complexity shapes user pre-use decisions. As such, it would be worthwhile to add to the above-mentioned dialogue by examining the role of visual complexity in the mobile app pre-use context by evaluating the underlying mechanisms through which it might influence the decision to download an app. In this regard, the present study proposes that since emotions are often elicited from visual design components (Bhandari et al., 2019) and it is widely known that emotions are critical in shaping user behaviours (Bhandari et al., 2019; Ding, 2018; Verkijika, 2020), emotions could play a key mediating role in explaining the link between visual complexity and the intention to download a mobile app.

The present study focuses on two future-oriented emotions (i.e. hope and anticipated regret) which are critical in consumer decision-making but are less explored in the information systems context (Ding, 2018; Verkijika, 2020). The measurement of these two future-oriented emotions within the mobile app context is well-grounded (Ding, 2018; Verkijika, 2020) and these emotions are likely to be elicited from visual complexity stimuli. Additionally, since users might often regret choosing complex apps after they start interacting with the app, they might likely look for clues on whether or not it is worthwhile exploring a given visually complex app. As such, this study proposes feature overload as a possible boundary condition when examining the mechanism through which visual complexity influences mobile app download via the mediating role of future-oriented emotions. This is because feature overload can easily signal poor quality which might reduce a user's desire to download a visually complex app.

The rest of the paper is structured as follows: Section 2 presents a review of extant literature, highlighting the gaps addressed by this study, the overarching theoretical framework, and the development of hypotheses. Section 3 presents information on the methodology and data with a focus on the sample, data collection, measures, and the demographic profile of respondents. Section 4 shows the analyses, presents the results and discusses the findings. Finally, section 5 presents the conclusion and implications of the study.

2. Theory, literature review and research hypotheses

2.1. Literature review

Visual complexity has been a widely studied phenomenon over the years with most of its initial foundations emerging form the visual aesthetics literature (King et al., 2020). In the information systems context, visual complexity is a vital factor that influences several aspects of a user's interaction with an information system. Visual complexity shapes user perceptions about a system and help form their initial impressions about the system as well as their post-use appraisal of the system (Eytam et al., 2017; King et al., 2020). The effect of visual complexity on an information system is highly dependent on the usage context when the user evaluates the system. Generally, visual complexity tends to have favourable outcomes in the pre-use context but negative effects in the post-use context (Eytam et al., 2017; King et al., 2020; Tuch et al., 2012; Sohn et al., 2017). This is because users are generally attracted to complex systems due to the potential functionality they might offer, however, when they start using the complex system, they might easily find it hard to use which decreases their satisfaction in the complex system. As such, for technology providers, initially presenting a system with adequate visual complexity can be seen as an appropriate strategy to attract initial users.

While visual complexity might be instrumental in the pre-use context (Eytam et al., 2017; Karr-Wisniewski & Lu, 2010), little is known about the mechanisms through which this happens (King et al., 2020). Research over the years has emphasised the fact that visual complexity could be maximized by system providers to enhance the overall initial impression that users have about their systems to enhance possible adoption. Yet, with little evidence available on how complexity translates to adoption behaviour, system providers are left with a limited understanding of how to effectively translate complexity to initial adoption. In the context of webpages, King et al. (2020) recently presented a mechanism through which visual complexity influence users first impressions of websites. The present study adds to this domain by focusing on mobile apps and presenting another unique mechanism for explaining the positive influence of visual complexity in the pre-use context.

2.2. Theoretical framework

The present study is grounded in the Stimulus-Organism-Response (S-O-R) framework by Mehrabian and Russell (1974). While these authors initially developed this framework for the environmental psychology context, it has been widely validated for use in other contexts, including information systems. The underlying assumption of the S-O-R is that environmental cues shape behavioural outcomes through the stimulation of cognitive and affective responses (Chang et al., 2014; Tang et al., 2019). There are three key components in the SOR framework namely the stimulus, the organism and the response. The stimulus refers to the environmental cues that arouse a person. The organism refers to the internal processes (e.g. cognitive and affective states) that occur when an individual is aroused by the stimuli, while the response depicts the behavioural outcome that characterises an individual's reaction to the stimuli and organism (Tang et al., 2019).

The S-O-R is suitable in this study for the following reasons. Firstly, visual stimuli have been widely shown to be a vital environmental cue that shapes information system-related behaviours through the stimulation of affective responses as proposed in the S-O-R. For example, using the S-O-R framework, several studies (e.g. Chang et al., 2014) have shown that visual aesthetic is a valuable visual stimulus that serves as the needed environmental cue in the S-O-R framework to shape behavioural outcomes. Like visual aesthetics, visual complexity is also one of the widely known visual stimuli in the information systems context (Kumar et al., 2018). Additionally, visual complexity can influence an individual's emotional state to shape their behaviours towards a system (Kumar et al., 2018; Lee et al., 2019). As such, visual complexity can be considered to be a relevant stimulus for use in the S-O-R framework.

Secondly, the present study suggests future-oriented emotions as the mediating factor that translates the visual complexity stimulus to a given behavioural outcome. As already indicated, emotions are a fundamental part of the internal state (i.e. organism) in the S-O-R framework that consequently shape behaviours. Future-oriented emotions refer to emotional states that are elicited in response to a future event (Baumgartner et al., 2008). These emotions are generally classified as either anticipatory or anticipated. Anticipatory emotions (e.g. hope or fear) characterise the emotional state that an individual currently experience due to the prospect of an expected future event which could be desirable or not (Baumgartner et al., 2008; Bettiga & Lamberti, 2020). For example, a person can have hope now that a decision to adopt a given information system will yields benefits in the future while another might experience fear now that the decision to purchase a selected information system might be a waste of money. On the other hand, anticipated emotions (e.g. anticipated regret and anticipated happiness) refer to emotional states that a person might project to experience in future events that can either be desirable or undesirable (Baumgartner et al., 2008; Bettiga & Lamberti, 2020). For example, an individual might anticipate that failure to adopt a given technology might lead to regret in future while others might anticipate experiencing happiness from adopting the system in future. There is growing evidence suggesting that both anticipatory and anticipated emotions play a vital role in consumer decision making, including behavioural decisions relating to information systems (Ding, 2018; Verkijika, 2020). In this regard, the present study selected one anticipatory (i.e. hope) and one anticipated (i.e. anticipated regret) emotion that is likely to shape information systems behaviour based on evidence from prior studies (Ding, 2018; Verkijika, 2020). As such, the present study proposes that these two future-oriented emotions are likely to act as the internal state that translates the visual complexity stimulus to achieve the desired behavioural response (i.e. intention to download a mobile app).

Lastly, extant evidence indicates that the relationship between the stimulus and organism is sometimes characterised by boundary

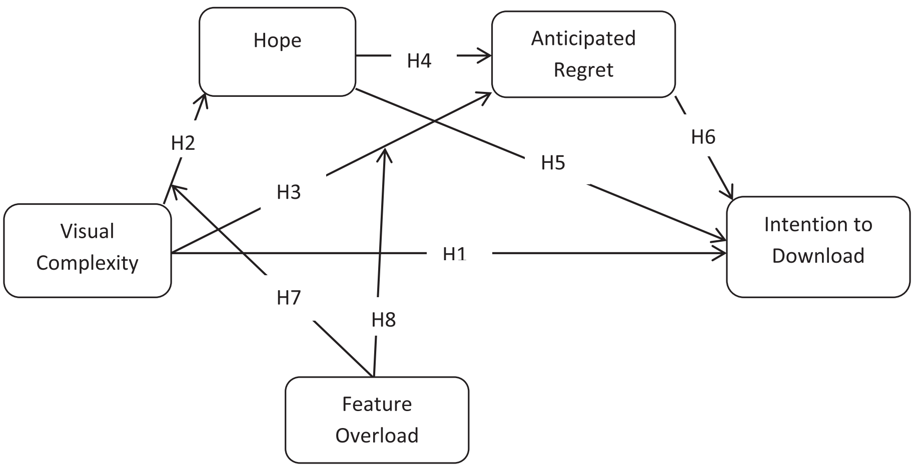

Fig. 1. Proposed model.

conditions. This follows from prior studies (e.g. Cheah et al., 2020; Wang et al., 2018) that have shown significant moderating effects of various factors on the relationship between various stimuli and organisms within the S-O-R framework. Similarly, the present study postulates that the relationship between visual complexity (i.e. stimulus) and future-oriented emotions (organism) might have some boundary conditions. As such, feature overload is proposed as one such possible boundary condition. This is because feature overload has the potential to affect the extent to which visual complexity stimulates the selected future-oriented emotions. Despite the benefits of visual complexity in the pre-use context, feature overload can easily signal poor quality (Marciuska, Gencel & Abrahamsson, 2014) and in some cases, users can judge that the cost of learning all the overload features might outweigh the benefits of the system (Lee, Son & Kim, 2016). This can likely have a consequence on their emotional reaction to the potential benefits from the visually complex system. Thus, feature overload is proposed to have a significant moderating effect on the relationship between visual complexity and the selected future-oriented emotions. The proposed model is presented in Fig. 1.

2.3. Development of hypotheses

2.3.1. Visual complexity

Visual complexity generally refers to the overall visual richness of an interface and is often characterised by the existence of diversity and number of elements/features in an interface (Herzog & Leverich, 2003; Kumar et al., 2018; Lee et al., 2019). About two decades ago, Brown and Carpenter (2000) noted that adding more features to an interface makes the system look more proficient. This is often vital in the pre-use context as potential users often tend to perceive high visual complexity to mean greater functionality, which enhances their desire to choose overly complex systems (Eytam et al., 2017). Also, when an interface is visually complex, some users tend to perceive it as having a good aesthetic appeal which thus enhances user desires to explore the system (Brunner-Sperdin et al., 2014; Kumar et al., 2018).

From an S-O-R perspective, complexity is often considered to be a vital visual stimulus that elicits affective responses in users. Users often perceive visually complex interfaces to require more involvement and this fosters interest in the system as high levels of involvement is often perceived to result in more enjoyment (Kumar et al., 2018). This view has been supported by Kumar et al. (2018) who showed that visual complexity was positively related to perceived enjoyment. According to Lee et al. (2019), visual complexity stimulates both valence and arousal which are core dimensions of emotions. As such, the visual complexity of a mobile app is likely to elicit future-oriented emotions as these emotions are valenced (i.e. positively or negatively) emotions (Baumgartner et al., 2008). For example, a mobile app interface that provides more functionality is likely to elicit hope as users will believe that such a product would possible meet their needs. Similarly, since individuals weigh more on functionality in the pre-use context (Eytam et al., 2017), a visually complex app will elicit feelings of anticipated regret because if users choose an app with limited functionality and later require one with more features, they might easily regret choosing the app. As such, high visual complexity will likely be the most preferred option for minimizing the possibility of future regret (Eytam et al., 2017). Following from the above, this study hypothesizes that:

H1: Visual complexity will have a significant positive influence on the intention to download a mobile app

H2: Visual complexity will have a significant positive influence on hope

H3: Visual complexity will have a significant positive influence on anticipated regret

2.3.2. Hope

Hope is a positive emotion that individuals experience when they are convinced of the possibility of a satisfactory future outcome despite the indeterminate nature of future events (Ding et al., 2018; Gabillet et al., 2020). Hope can also be seen as a positive emotional state that motivates an individual to act towards achieving a given goal (Long et al., 2020). This is because hope echoes the possibility of experiencing pleasure/satisfaction from a given future outcome (Baumgartner et al., 2008). As such, when people are hopeful about future beneficial outcomes from using a given information system, they will be more likely to adopt and use the system. This view has been supported by extant studies which show that hope translates into behavioural intentions towards the use of information systems (Bukchin & Kerret, 2020; Ding, 2018). This is because hope is often likely to incentivise user engagement in taking a specific cause of action while hopelessness increases the likelihood of inaction (Park et al., 2020). Additionally, hope often results in a more optimistic evaluation of a future event (Septianto et al., 2020). As such, since individuals often act in a manner that minimizes the possibility of future regret (Ding, 2018; Verkijika, 2020) moving in the direction of hope might seem more feasible. This is because hopeful consumers will primarily focus on imagining positive experiences (Septianto et al., 2020) and people are generally known to act in congruence with their affective response (Baumgartner et al., 2008). Following from the above discussion, one will expect that an individual who is hopeful about the possible benefits/positive experiences from using a given mobile app will be more likely to anticipate regret from failing to explore the app and will, therefore, develop the intention to download and try it. Hence, this study hypothesises that:

H4: Hope will have a significant positive influence on anticipated regret

H5: Hope will have a significant positive influence on the intention to download

2.3.3. Anticipated regret

Anticipated regret encompasses the expectation of dissatisfaction if the future outcome of a choice made now were to be revealed (Ding, 2018; Shih & Schau, 2011). The regret literature emphasises that all behavioural choices are characterised by an element of regret and that these behavioural choices are mostly made in the direction of minimising the likelihood of future regret (Ding, 2018; Verkijika, 2020). This is often achieved by evaluating the possibility of future regret associated with a given behavioural outcome and then making present decisions that will minimise the occurrence of such regret (Carfora, Caso & Conner, 2017; Ding, 2018; Verkijika, 2020). In the pre-use context of technology adoption, the decision to adopt or not to adopt a given technology is also associated with an element of regret. Technology adoption is often likely to be motivated by the desire to minimise any possible regret from missing out on the benefits of a given technology (Shih and Schau, 2011; Verkijika, 2020). If an individual believes that a given technology might be valuable, the person is likely to experience a high level of regret associated with inaction because failure to try the technology will mean failure to experience the potential value that could have been derived from the technology. As such, following from the regret theory, the most probably cause of action that minimises future regret will be to adopt and try the technology. This view has been supported by prior studies which have shown that anticipated regret has a significant positive influence on the adoption of mobile payments (Verkijika, 2020) and the continuance use of mobile devices (Ding, 2018). As such, it will also be expected that an individual who experiences a high level of anticipated regret regarding a given mobile app will be more likely to adopt and try the mobile app. Thus, this study hypothesises that:

H6: Anticipated regret will have a significant positive influence on the intention to download a mobile app.

2.3.4. *The role of feature overload*

Feature overload generally depicts a context in which a given technology is overly complicated for a given task, or when “the addition of new features is outweighed by the impact on technical resources and the complexity of use” (Karr-Wisniewski & Lu, 2010, p.1062). Feature overload also commonly characterises a situation where the provided features exceed user needs (Thompson, Hamilton & Rust, 2005; Zhang et al., 2016). This is often in most cases a consequence of feature creep which entails the act of increasingly adding features to a system such that the system inevitably becomes confusing and diminishes the user experience (Winkler, 2001). In most cases of feature overload, the system ends up with many low-value features and since users get low value from the system, they tend to switch to less complex products with better value propositions (Marciuska et al., 2014). Additionally, feature overload can often bloat an interface thus making it slower to load (Marciuska et al., 2014; Xu et al., 2010) and this can frustrate users and significantly lower the user experience.

While in the pre-use context of information systems, additional features can signal superior functionality and attract users to adopt the technology (Eytam et al., 2017; Karr-Wisniewski & Lu, 2010), users are also likely to be concerned about the cognitive load required to use the system (Karr-Wisniewski & Lu, 2010; Lee et al., 2016). This is because when users perceive that the cost of learning the numerous features might outweigh the benefits, such as system will be seen as a source of fatigue (Lee et al., 2016). As such, users might become less hopeful about the potential benefits of the technology given the possible psychological strain that could be experienced from the feature fatigue. Similarly, if the system is perceived to have many low-value features that might not be needed by the user, this might reduce the users hope in the potential benefits of the system as the provision of many low-value features might signal poor system quality. Additionally, users often adopt technology to satisfy their needs, and as such, they would look for systems that can meet their demands. However, with feature overload, a system will have many features that basically will not be used by a user (Guo et al., 2020). As such, the anticipated regret of not using the system will likely be low as the user already perceives that some or most of the features would not be needed. This is because users mostly anticipated regret when they are likely to miss out on the benefits of some features (Ding, 2018; Verkijika, 2020). However, a user is unlikely to miss out on benefits from features perceived as having low value or being less likely to be used. Following from the above, it is expected that feature overload would moderate the relationship between visual complexity and future-oriented emotions (i.e. hope and anticipated regret) such that the two emotions will be less pronounced when feature overload is high. Thus this study hypothesises that:

H7: The relationship between visual complexity and hope will be moderated by feature overload such that the effect will be lower when feature overload is high.

H8: The relationship between visual complexity and anticipated regret will be moderated by feature overload such that the effect will be lower when feature overload is high.

3. Methodology and data

3.1. *Sample and data collection*

This study employed a single-group post-test only design to gather the data for testing the relationships outlined in the proposed model. Four mobile apps were used as the stimuli for the present study. As argued by Kumar et al. (2018) the choice of using real apps enhances the realism and quality of the data. Since the sample used in this study was students, the category of apps selected for the study was chosen to fit the sample. The study thus made use of four student time management apps. Three interfaces from each app that were used by the app developers to advertise the app on the Google Play Store, were selected for the experiment. These three interfaces which are publicly available to users before they download the apps provide an overall view of the app thus enabling a user to make a decision regarding the perceived visual complexity of the app in the pre-use context. There were 84 similar apps for student time management. As such, the selection of the four related apps for this study was manipulated to ensure that apps selected provided different levels of visual complexity. This was evaluated in a pre-study with ten participants who rated the visual complexity of 8 shortlisted apps using the visual complexity scale in Appendix A. From their evaluation, four apps with notable differences in the level of visual complexity were selected for the study. These ten participants did not take part in the final study. The study experiment was conducted in July 2019.

Participants for the experiment were recruited through a combination of convenience and snowball sampling techniques. Convenience sampling was implemented by using a contact list of students who had previously provided their contact details and indicated their willingness to be contacted in future when a research study is being conducted. The networks of those who responded positively to the call were then used to recruit other students in a snowball approach as these students circulated the project information sheet in their networks and interested students used the contact information to book a session in the experiment. The recruited students came from diverse disciplines in the university. No monetary rewards were provided for participation in the study. A gatekeeping question was used to ensure that only students who were interested in time management apps participated in the study. This was meant to eliminate participants who might make a behavioural choice simply because they are not interested in such an app. Each participant was randomly assigned to one app to evaluate and decide he/she would like to download it or not. Participants only evaluated apps that they had not previously experienced before. If the participant had been exposed to a given app before, a different one was randomly selected. Each participant was exposed to the three interfaces of the selected app for a period of three minutes. This was considered to be enough time to evaluate the visual stimuli (e.g. Bhandari et al., 2019). All the participants used the same device to view the interfaces. Afterwards, the participants completed a questionnaire that evaluated the visual complexity and feature overload of the app, their subjective future-oriented emotional reactions to the app (i.e. hope and anticipated regret), and their intention to download.

3.2. Measures and demographic data

Visual complexity was measured using three items adapted from Lee et al. (2019). Feature overload was measured using three items adapted from Karr-Wisniewski and Lu (2010). While items for hope (3-items) and anticipated regret (2-items) were adapted from two studies (Ding, 2018; Verkijika, 2020). The intention to download the app was measured using 3 items adapted from Bhandari et al. (2019). All the items are indicated in Appendix A. A total of 218 participants took part in the study. The demographic profile of the participants is presented in Table 1.

4. Analyses, results and discussion

4.1. Analyses of common method variance

Common method variance (CMV) was assessed using Harman's one-factor test and the full collinearity test. To conduct Harman's one-factor test, all the items used to measure the constructs in the proposed model were subjected to a factor analysis to determine whether the variance in the data could be mainly accounted for by a single factor (Changet al., 2010). The highest factor loaded with an Eigenvalue of 4.549 and accounted for 40.85% of the variance. Since the first factor accounted for <50% of the variance and the items did not load on a single factor, CMV was therefore not a cause for concern in the present study. In addition, the full collinearity test proposed by Kock and Lynn (2012) was also used to further ascertain the absence of CMV in this study. This test was conducted using SmartPLS software. The full collinearity test is conducted by "creating a block where all latent variables in the model are included as predictors pointing at one single criterion" (Kock and Lynn, 2012, p. 558). The single criterion represents a latent variable that is fully created using randomly generated values. To assess the existence of CMV, the variance inflation factor (VIF) values of the constructs is evaluated after running the model using partial least squares structural equation modelling (PLS-SEM). VIF values above 3.3 suggest that CMV is a possible concern (Kock & Lynn, 2012). After running the model, VIF values of 1.635, 2.326, 2.417, 1.672 and 1.424 were obtained for visual complexity, hope, anticipated regret, feature overload and intentions to download respectively. This further confirmed that CMV was not a concern for this study as all the VIF values were below 3.3.

4.2. Analyses of construct reliability and validity

Reliability and validity were evaluated in line with general methodological recommendations. Cronbach's alpha and composite reliability values were used to assess the reliability of the constructs. As seen in Table 2, the Cronbach's alpha values ranged from 0.742

Table 1
Profile of participants.

	Frequency	Percentage
Gender		
Male	115	52.8
Female	103	47.2
Age group		
18–20 years	85	39.0
21–25 years	110	50.5
Above 25 years	23	10.6
Smartphone experience		
<12 Months	9	4.1
13–24 months	25	11.5
More than 24 months	184	84.4
Average Apps Installed (Past Year)		
1–5	23	10.6
6–10	48	22.0
More than 10	147	67.4

to 0.845 while composite reliability values ranged from 0.814 to 0.907. All these values were above the recommended threshold of 0.7 (Hair, Hult, Ringle & Sarstedt, 2017) thus confirming the reliability of the constructs. Convergent validity was assessed using the average variance extracted (AVE) while discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT). The AVE values ranged from 0.674 to 0.802, thus confirming the convergent validity of the constructs as all were above the recommended threshold value of 0.5 (Hair et al., 2017).

The HTMT values for assessing discriminant validity are presented in Table 3. HTMT values depict the disattenuated correlation between any two constructs and any value <0.9 supports discriminant validity (Verkijika & De Wet, 2018). From Table 3, it is seen that HTMT values ranged from 0.302 to 0.786. This confirms the discriminant validity of the constructs as all the values are below the threshold of 0.9 or even the conservative threshold of 0.85 (Verkijika & De Wet, 2018)

4.3. Testing of hypotheses

The testing of the hypothesised associations was conducted using the PROCESS macro for SPSS version 3.3 (Hayes, 2017). The analysis was based on PROCESS model 84 which allows for simultaneous assessment of all the hypothesized associations as presented in the conceptual model (Fig. 1) along with insights regarding the moderated mediation of the indirect effects. The results pertaining to the hypothesized relationships are provided in Table 4.

The results in Table 4 follow a three-step approach used by PROCESS model 84. In the first step, the relationship between visual complexity and hope is assessed along with the moderating effect of feature overload. The results show that visual complexity has a positive effect on hope ($B = 0.49$, $p < 0.01$) and that the relationship is negatively moderated by feature overload ($B = -0.10$, $p < 0.01$). Besides being a moderating factor, feature overload has a significant negative effect on hope ($B = -0.08$, $p < 0.05$). In the second step, the influence of visual complexity and hope on anticipated regret was examined along with the moderating role of feature overload on the visual complexity to anticipated regret relationship. The results showed that both visual complexity ($B = 0.27$, $p < 0.01$) and hope ($B = 0.51$, $p < 0.01$) were positive and significantly associated with anticipated regret. Additionally, feature overload had a negative effect on anticipated regret ($B = -0.28$, $p < 0.01$) and also negatively moderated the relationship between visual complexity and anticipated regret ($B = -0.10$, $p < 0.05$). The third step evaluated the direct effects of visual complexity, hope and anticipated regret on the intention to download a mobile app. The results showed that hope ($B = 0.63$, $p < 0.01$) and anticipated regret ($B = 0.27$, $p < 0.05$) had significant positive effects on the intention to download a mobile app, however, the effect of visual complexity was not significant ($B = 0.12$, $p > 0.05$). The results in Table 4 are summarised in line with the hypothesised relationships (Fig. 1) and presented in Fig. 2. From Fig. 2, it is seen that out of the 8 hypotheses, 7 were confirmed and only one was not (i.e. hypothesis H1).

4.4. Conditional indirect effects

In addition to the results relating to the hypothesised associations (Table 3 and Fig. 2) the PROCESS macro model 84 also provide valuable insights to further probe the nature of the conditional indirect relationships. These insights are vital in providing an understanding of the mechanism through which visual complexity affects the intention to download a mobile app. The conditional indirect effects from the analysis (PROCESS model 84) are presented in Table 5.

From Table 5, it is observed that that indirect effect of visual complexity on the intentions to download via hope (Visual complexity – > Hope – > Intention to Download) is significant for both high (effect = 0.239, 95% CI [0.161; 0.325]) and low (effect = 0.369, 95% CI [0.270; 0.392]) levels of feature overload. Additionally, this indirect effect is significantly moderated by feature overload such that the effect weakens as feature overload increases (index = −0.049, 95% CI [−0.089; −0.014]). Similarly, the indirect effect of visual complexity on the intentions to download via anticipated regret (Visual complexity – > Anticipated Regret – > Intention to Download) is positive and significant for both high (effect = 0.033, 95% CI [0.005; 0.072]) and low (effect = 0.104, 95% CI [0.030; 0.190]) levels of feature overload. Also, the indirect effect is moderated by feature overload such that the effect weakens as feature overload increases (index = −0.027, 95% CI [−0.049; −0.008]). Lastly, the serial mediation effect that links visual complexity to intentions via hope and anticipated regret (Visual complexity – > Hope – > Anticipated Regret – > Intention to Download) was significant for both high (effect = 0.050, 95% CI [0.016; 0.089]) and low (effect = 0.077, 95% CI [0.020; 0.111]) levels of feature overload. More so, this serial mediation was significantly moderated by feature overload such that the effect is weaker when feature overload increases (index = −0.010, 95% CI [-0.023; −0.002]). These findings confirm three indirect routes through which visual complexity positively influences the intention to download a mobile app, all of which are moderated by feature overload. This supports the growing literature on the important role of hope and anticipated regret is shaping various behavioural outcomes associated with information systems (Ding, 2018; Shih and Schau, 2011; Verkijika, 2020).

Table 2
Reliability and convergent validity.

	Cronbach's Alpha	Composite Reliability	AVE
Anticipated Regret (AR)	0.831	0.902	0.764
Feature Overload (FO)	0.812	0.844	0.710
Hope (HO)	0.845	0.907	0.802
Intention to Download (ID)	0.742	0.814	0.674
Visual Complexity (VC)	0.817	0.886	0.723

Table 3
Discriminant validity based on the HTMT.

	AR	FO	HO	ID
FO	0.571			
HO	0.728	0.312		
ID	0.695	0.333	0.786	
VC	0.733	0.302	0.718	0.658

Table 4
Results of the hypothesised relationships (PROCESS model 84).

Step 1: 1st mediator variable model	Dependent Variable: Hope (HO)					
	Coeff.	*SE*	*LL*	*UL*	*t-value*	*R^2*
						0.40
H1: Visual Complexity (VC)	0.49	0.05	0.39	0.58	10.52**	
Feature Overload (FO)	−0.10	0.04	−0.18	−0.02	−2.47*	
H7: VC × FO	−0.08	0.03	−0.14	−0.02	−2.56*	
Step 2: 2nd mediator variable model	Dependent Variable: Anticipated Regret (AR)					
	Coeff.	*SE*	*LL*	*UL*	*t-value*	*R^2*
						0.64
VC	0.27	0.05	0.17	0.37	5.20**	
HO	0.51	0.06	0.38	0.63	8.19**	
FO	−0.28	0.04	−0.35	−0.21	−7.59**	
VC × FO	−0.10	0.03	−0.16	−0.05	−3.72**	
Step 3: Outcome variable model	Dependent Variable: Intention to Download					
	Coeff.	*SE*	*LL*	*UL*	*t-value*	*R^2*
						0.46
VC	0.12	0.09	−0.06	0.30	1.34	
HO	0.63	0.12	0.39	0.86	5.21**	
AR	0.27	0.10	0.06	0.46	2.52*	

Note. **p < 0.01;*p < 0.05; LL and UL represents the lower and upper bounds of the bootstrap confidence interval [95%].

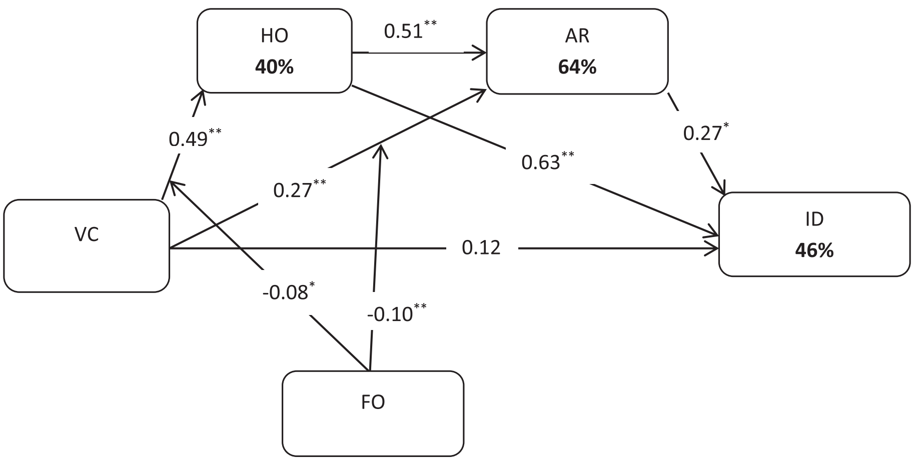

Fig. 2.

5. Conclusion

Mobile apps have become an integral part of our lives. While this is good news for app developers and publishers, the high competition in the app market makes it difficult for most apps to capture user interest as users are increasingly selective of apps to use. As such, the present study adds to the ongoing literature (e.g. Bhandari et al., 2019; Lin & Chen, 2019) that attempts to understand why some apps gain customer attention given the polarised nature of mobile app downloads. The present study showed that visual complexity could positively affect user intention to download a mobile app by stimulating two future-oriented emotions (i.e. hope and anticipated regret). Additionally, the relationship is moderated by feature overload. Besides the direct relationship between visual complexity and the intention to download (i.e. H1), all the other hypothesized relationships are primary as they provide new evaluations of the mechanism through which visual complexity might influence the intention to download a mobile app.

Table 5
Conditional indirect effects of visual complexity.

Conditional Indirect Effects	Dependent Variable: Intention to Download			
	Effect	*SE*	*LL*	*UL*
Visual complexity – > Hope – > Intention to Download				
High feature overload	0.239	0.042	0.161	0.325
Low feature overload	0.369	0.055	0.270	0.392
Index of moderated Mediation	*−0.049*	*0.019*	*−0.089*	*−0.014*
Visual complexity – > Anticipated Regret – > Intention to Download				
High feature overload	0.033	0.018	0.005	0.072
Low feature overload	0.104	0.041	0.030	0.190
Index of moderated Mediation	*−0.027*	*0.011*	*−0.049*	*−0.008*
Visual complexity – > Hope – > Anticipated Regret – > Intention to Download				
High feature overload	0.050	0.018	0.016	0.089
Low feature overload	0.077	0.029	0.020	0.111
Index of moderated Mediation	*−0.010*	*0.006*	*−0.023*	*−0.002*

Notes. The effects are significant when the LL and UL of the 95% confidence interval does not straddle zero.

These findings have several implications. From a practitioner perspective, this study provides numerous insights. Firstly, it is widely known that the mobile app market is extremely competitive with similar apps competition for user attention. Since in the pre-use context, potential users often see the advertised interface of apps before downloading them, app providers should focus on advertising the sections of the interface that appears visually complex as this is likely to trigger future-oriented emotions that will influence the behavioural intentions to download the apps. However, this should not be done blindly as it is imperative for the app providers to first test this advertised interface with users to ensure that it triggers desired future-oriented emotions before using the selected interface for advertising the app. Secondly, the fact that future-oriented emotions have a direct effect on the intention to download mobile apps further suggests the need to find ways of enhancing the elicitation of these emotions from advertised apps. Visual complexity alone explains only a limited percentage of variance in hope and anticipated regret so app providers should consider finding others ways of eliciting these emotions. This can be done by using the S-O-R to identify relevant environmental cues that can act as a stimulus for these emotions (e.g. design elements, product description, customer reviews etc.). Additionally, design elements should be carefully selected to ensuring that the features included in the complex user interface are those that meet or exceed user expectations (Ding, 2018). Lastly, mobile app providers should carefully evaluate the feature overload of their app interfaces because while users might be attracted to the visual complexity of their interfaces in the pre-use context, they are less likely to go for those that appear to be characterised by feature overload. Mobile app interfaces characterised by high feature overload might be considered as low quality and will have a negative effect in stimulating the future-oriented emotions vital for fostering the intentions to download the mobile app.

From a policy perspective, it is imperative for organizations developing interface design guidelines to invest in research and development of guidelines for mobile app interfaces especially concerning the visual complexity and feature overload of the interface. It is imperative for designers to have guidelines that can help them to create mobile apps that are visually complex enough to attract users (via stimulation of future-oriented emotions) while ensuring such interfaces are not overloaded with features. Also, with recent advances in technology, there is emerging evidence of automated tools for predicting the visual complexity of web interfaces (Michailidou et al., 2021). Public organizations focusing on the design of mobile apps should also consider investing in developing similar tools for evaluating the visual complexity of mobile app interfaces and make such tools publicly available for app developers to use.

From a theoretical perspective, the implications for research are twofold. Firstly, this study highlights the role of visual complexity in decisively shaping behavioural outcomes. Prior research (Eytam et al., 2017; Karr-Wisniewski & Lu, 2010) has highlighted the view that visual complexity is an important factor in the pre-use context of information systems. This is because potential users easily weigh their decisions more towards functionality and tend to perceive a visually complex system to provide more functionality (Eytam et al., 2017). While prior studies have been instrumental in providing insights on why individuals might choose overly complex systems, little has been known about the underlying mechanisms through which this happens. This study provides insights into the role that future-oriented emotions play in translating perceptions of visual complexity to behavioural outcomes in the context of mobile apps. The findings show that the relationship between visual complexity and the intentions to download a mobile app is not direct, but rather indirectly through the mediating role of future-oriented emotions. This adds new knowledge to the increasing visual complexity research by showing the mechanism through which visual complexity affects behavioural intentions. Additionally, this outcome contributes to the growing literature (e.g. Ding, 2018; Shih & Schau, 2011; Verkijika, 2020) that recognises the imperative role of future-oriented emotions in shaping behavioural outcomes.

Secondly, while the indirect effect of visual complexity on behavioural intentions is significant, the effect is, however, moderated by feature overload. The research on system overload in recent years has mostly focused on information overload with little attention paid to other aspects of system overload like feature overload and communication overload (Karr-Wisniewski & Lu, 2010). However, this study showed the need to consider the role of feature overload as a moderating factor that shapes behavioural outcomes. The findings provide two imperative insights namely: (1) in the visual complexity literature, the indirect effect is influenced by feature overload such that the desired effect on behavioural outcome is weaker when feature overload is high. This boundary condition provides the impetus for researchers to carefully analyse and present robust evaluations of the mechanism through which visual complexity influences behavioural outcomes in the pre-use context. (2) The moderating role of feature overload highlights the imminent role of this system overload dimension in the information systems behaviour literature. Using this as a starting point, researchers can better examine the role of feature overload in shaping other behavioural outcomes. For example, besides its role as a moderator, feature overload can significantly reduce user experience of desired future-oriented emotions (see Table 4) which possibly shows its role when evaluating how future-oriented emotions shape behavioural outcomes.

While these findings several implications, it is also imperative to acknowledge some limitations of the study. Firstly, the evaluated interfaces were limited to a single category. Since different categories might have different aspects of visual complexity and feature overload, it would be imperative to test the proposed model across other categories to enhance the generalizability. Secondly, only two future-oriented emotions were considered, as such, future studies might generate more insights from evaluating more future-oriented emotions. Lastly, the role of visual complexity is this study is limited to the pre-use context without examining the possible negative effects of visual complexity post-adoption. Future studies can attempt to examine the role of visual complexity from the pre-use to the post-adoption (e.g. continuance use) context to provide insights that can help reduce the churn rate from users who might start experiencing the negative effects of visual complexity post-adoption.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Items	Source
Visual Complexity	
• The mobile app seems to contain a good variety of components/features that will keep me involved.	Lee et al., 2019
• I feel drawn in by the variety of information or components the mobile app offers.	
• The mobile app interface looks very complicated and appears dense	
Feature Overload	
• The mobile app seems to have some features that are not necessary for what I will likely be using it for.	Karr-Wisniewski & Lu (2010).
• The mobile app interface is poorly designed because of the many features that seem to bloat the interface.	
• Some features of this mobile app look more complex than the tasks that I have to complete using the apps	
Hope	
• I feel confident that the app will bring me more benefits in the future	Ding (2018)
• I am optimistic that it will be increasingly useful in my life	
• I am hopeful that it will be more popular than it is today	
Anticipated Regret	
• There is a high probability that I will regret it if I failed to download and try this app	Ding (2018) and Verkijika (2020)
• I would feel very worried if I did not download and try this app	
Intention to Download	
• I intend to download and try this app	Bhandari et al., 2019
• I am likely to download and try this app	
• I am certain that I will download and try this app	

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