A time-stamped and multi-class Ekman mood theory analysis of Octogenarians perspectives on M-Health

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Abstract

Healthcare service delivery continue to witness disruptive technological innovations through the instrumentality of mobile health applications in an attempt to achieve the universal health coverage goal. Several studies have appraised the technology acceptance tendencies of the innovation and as well as the rate of diffusion of the novelty into the core of the healthcare services domain. State-of-the-arts likewise have adopted sentiment analysis for the opinion mining of end users on the applications on everyday use. However, aforementioned studies seldom factor in the interests of technology-savvy Octogenarians who employs the services of the mobile health technologies. Hence, this study employs the Paul Ekman's emotional theory to analyze a time-stamped real-time opinions of Octogenarians to classify their emotional mood within a timeline thereby unravelling the spontaneity of their moods during the course of using mobile health applications. Experimental result returned *Surprise, Joy and Fear* as the only classes of Ekman's postulations exhibited by the Octogenarians with *Surprise* as the most dominant throughout the timeline despite being exhibited by only four respondents out of the entire population.

Keywords: M-Health, Octogenarian, Paul Ekman, Emotional analysis

1. Introduction

Efficient healthcare delivery is a basic necessity of the global society nonetheless the socioeconomic status of the geographical community. The delivery of healthcare services and the quality of service could be defined as the degree to which healthcare services increases the realization of expected results. This evidence-based experience is imperative for realizing the Universal Health Coverage (UHC) indices. Moreover, quality healthcare has been severally described depicting *effectiveness*: availability of services to those who need them; *safe*: prevention of harm to the cared-for during service delivery; and *people-oriented*: which means the delivery of services that appeals to end users' values, inclinations, and requirements. It is notable that qualitative service could avert a likely half of all maternal and newborn deaths, as highlighted by the Lancet Commission of 2018 in the High Quality Health Systems report. In the Nigerian context, the report ranks Nigeria as the 142nd out of 195 countries on health systems performance regarding access and quality of care [1]. The two performance index speaks to the prompt availability and accessibility of healthcare (facilities and practitioners), and the derivable values from each engagement. Whereas the Nigeria's National Health Act accedes to healthcare for all Nigerians regarding basic minimum package, the supposed package is plagued by several impairments which deprives vulnerable demographics of basic services. The Act stipulates the Basic Minimum Package of Health Services to include a set of precautionary, promotive, defensive, curative, and rehabilitative services which are to be aided by the Basic Health Care Provision Fund (BHCPF) [2]. Notwithstanding Nigeria's treaty to the UHC, its healthcare delivery indicators shows total underperformance compared to countries with similar gross domestic product [3]. With a 2022 populace of about 216.7 million [4], the doctor to patient ratio of the country stands at 4:10000 in year 2022, in contrast to the World Health Organization (WHO) stipulated standard of 1:600 [5]. The dearth of domain experts in the industry has been usually ascribed to medical brain drain, a situation that further worsens the performance indices. Consequently, accessibility of service continues to evade the most vulnerable of the Nigerian society amongst other challenges. Industry experts have offered several recommendations to address the challenges including the deployment of an electronic healthcare (e-Health) management system which enjoys patronage across the globe [6]. Defined by the WHO as a cost-effective and dependable information technology lifeline for healthcare delivery [7], use case application areas of e-hHealth includes a Hospital Information Systems (HIS), Telemedicine, Electronic Medical Records (EMR) system, and Mobile Health (m-Health) system. They all offer disruptive technological solutions that has enhanced patient's safety initiatives through high precision rate, reduced cost, quality of healthcare delivery etc. [8]. Likely services on the e-Health platforms include prompt healthy-related information, e-prescription, clinical decision support systems, electronic health record system, telemedicine, diagnosis systems, etc. [9]. Furthermore, it is observed that clinical services improve appreciably with e-Health solutions, thereby reducing the average waiting time in 15 out of the total 19 centers surveyed for a survey by [10]. Consequent upon the foregoing, there is need to appraise the existing e-Health solutions that are operational in the Nigeria's healthcare system to avail software developers, policy makers, and end users of trends in terms of requirement specifications from the perspective of end users. Studies in literature have adopted different conceptual methodological frameworks to audit the e-Health industry from the perspective of end users. Observations indeed shows various models on Technology Acceptance Model (TAM) and Diffusion of Innovation Theory (DOI) especially in the healthcare industry. Other studies employed sentiment analysis tools on the opinions expressed by end users of M-Health applications in order to gauge their emotions with respect to ease of use, affordability, functionality, etc. However, the sentiment analysis approach is the most predominant in literature which identify polarities of end user emotions with respect to diverse factors. In those studies, opinions are mostly acquired from customers, social media platforms, and after-sale reviews of application users. However, these studies does not factor in the possibility of mood swings which is a function of the spontaneous circumstances surrounding product reviews. In addition, the demography of respondents whose opinions are sampled cannot be ascertained through the aforementioned sources. Therefore, there is a dire need for a study that targets a specific demography end user of M-Health applications in order to properly situate experimental observations. There is likewise the need to factor in the non-constant mood of reviewers, who might exhibit different emotional tendencies to different situational exigencies. This study therefore intends to answer the research question on whether the influence of time could result into a noteworthy spontaneity of emotional states towards the employment of M-Health applications. The aim of the study therefore intends to unravel the spontaneous emotional moods of Octogenarian end-users of M-Health applications within a specified timeline. The Ekman's sentiment analytical tool is employed in this study. the rest of the study is presented in the following ways. The theoretical and empirical literature review is presented in section 2. The conceptual methodological framework of the study is presented in section 3 while the experimental result is discussed in section 4. The conclusion and recommendations of the study is mentioned in

2. Literature review

Related studies are reviewed in this section on the adoption of the m-Health technology and user perception analysis. The theoretical and empirical review will present an overview of the subject matter. The theory on which this study is based include the Technology Acceptance Model (TAM), an information system theory which understands how technology end users have employed and deployed new disruptive technologies. The concept of the TAM was put forward by Davis (1989) xxxx to understand the acceptance of technology acceptance by users. Different studies in the medical domain including [11], [12], and [13] have deployed TAM to determine the acceptance level of m-Health by end users. The germane purpose of TAM is to determine the behavioral tendencies of users towards a new technology with respect to its perceived usefulness and ease of use [14]. The Diffusion of Innovation Theory (DOI) explains how a disruptive technology gains momentum with respect to a specified time period [15] which therefore triggers change in its domain area. Studies including [15] and [17] employed DOI in their studies for the introduction of m-Health applications in Mauritian context. In [16], the acceptance of consumer e-health innovations was studied through the development of an e-appointment scheduling service for a primary healthcare clinic. Data was acquired from the log records of patients and from interview of 125 of them. The overall adoption rate increased from 1.5% to 4% after 29 months of deployment. In [18], the TAM and DOI was employed for healthcare informatics technological solutions just as sentiment analysis is widely adopted as well for electronic health end users on user perception. Indeed, sentiment analysis in the healthcare domain is commonplace [19] with open source tool and commercially available software. Different subject areas were targets of the studies including public health [20], [21]; emergency [22]; disease treatment [23], [24] etc. a sentiment analysis of opinions on publicly available mobile solutions for asthma treatment was conducted by [25] by examining reviews of end users. From the sentiment analysis, issues associated with functionality and ease of use attracts negative sentiments unlike other considerations. In the work of [26], tweets diabetes were acquired for a sentiment analysis using SentiStrenght analyzer. It is observed that tweets with emoji shows more negative emotions than tweets with no emoji. The sentiment analysis of opinions on online healthcare platforms as it relates to quality of service was the main thrust of [27]. The Fast Large-Margin is used as the classification model and sentiment analysis for the service dimension labelling while the experimental result reviews that interaction quality attracts most positive sentiments from the users of the Alodokter M-Health application.

3. Materials and methods

This section presents the materials and methods used for the actualization of the study's proposed conceptual framework which is aimed at determining the spontaneous emotional trend of Octogenarians on the usage of M-Health solutions through the Ekman's emotional analytics. The diagrammatical demonstration of the relation existing between the variables under study is presented in the conceptual framework of this study in Figure 1. This study employed a quantitative and descriptive research methodology through collection of real-time primary data information from Octogenarians on their perception on e-Health solutions, to eventually determine their perception of the solutions through tests and analysis that produced time-stamped data for drawing conclusions.

3.1 Data acquisition

The study population specifically include opinions of Octogenarians whose responses to survey question returns an homogenous textual data that seeks to answer research questions set out for this study. These are end users of M-Health solutions in their old age with one medical conditions or the other that warrants constant need for healthcare service delivery. Purposive sampling approach is employed to acquire primary data from the Octogenarians in order to ensure only those with medical conditions and that uses M-Health services are included in the survey. This helps to target purposefully respondents with required and reliable information during data collection with respect to the study's objectives. Electronic questionnaire (Google form) tool was used for data collection which guarantee a greater extent of information standardization, and the link is sent periodically between 9th and 16th of May, 2022 to the recipients. They are enjoined to approach the link from time to time to express their opinions real time, with no limitations to numbers of times. The timestamp facility of the Google form is to capture the time factor of each opinion in real time which forms the basis of the research question of this study. The reliability of the data collection tool was guaranteed by subjecting the questionnaire to two respondents prior to carrying out the survey for critique and feedback which enhanced the tool prior to administration of the questionnaire. Validity of the tool was ensured by relying on medical expert opinions on the best possible ways to capture the questions having in mind the likely replies which must be able to measure intended indices.

3.2 Ekman's emotional modeling

The emotional theory of Paul Ekman [28] is employed in this study, which demarcates a 6-dimensional mood state cluster through text mining. The mood states are detected from each textual opinion that makes up the acquired corpus of this study. Ekman's seminal research is on the biological links of some particular sentiments in an attempt to show the universality and discreteness of emotions through the Darwinian method [25]. Hence, Paul Ekman theorized that basic human emotions (including happiness, anger, sadness, surprise, disgust, contempt, and fear) are inborn and common to diverse cultures which could be identified through expressions. The theory opines the cascading effects of the emotions across individual's expressions which provide clues as to the identification of the exact emotional state of people towards situations or things. Hence, human expressions are analyzed through the Paul Ekman's emotions theory based on the correlation between expressions and the descriptive elements of the Ekman's 6-state emotional categories. The Ekman's theory gauges emotions through content analytics for the six emotional states as described in Table 1. In this study, the profiling of the Octogenarians opinions is analyzed for a multi-class classification according to the Ekman's theory through the Orange data mining toolkit [26]. The profiler widget in the toolkit detects Ekman emotions in texts by accepting collections of documents (Octogenarian opinions) as input, returning a corpus with information on the emotional sentiments for each instance contained in the corpus, with respect to the different timelines. The spontaneous *emotion* variables will be observed through the Box plot widget of the toolkit in order to discover the emotional transitions with respect to M-Health usage by Octogenarians.

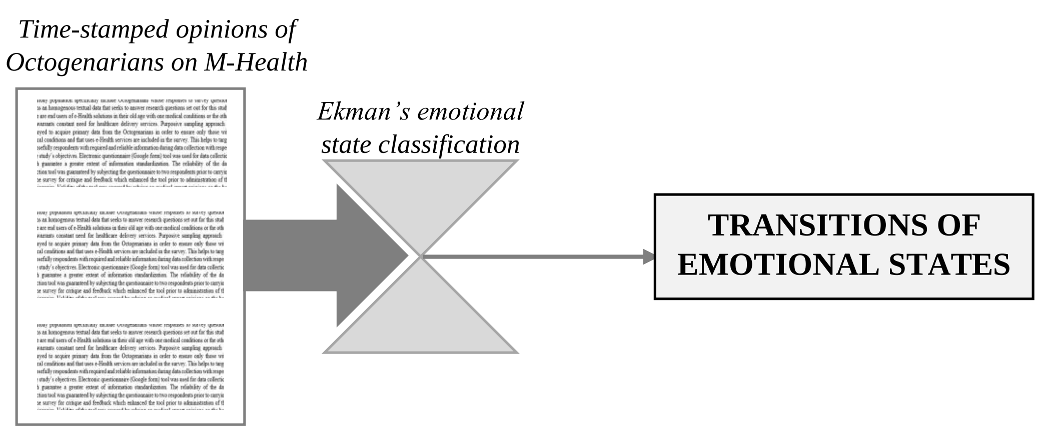

Figure 1: The conceptual framework of the study

Table 1: Descriptive analysis of Ekman's emotional states [22]

State	**Description**
Sadness	Characterized by feelings of hopelessness, disappointment, and grief
Happiness	Elicits feelings of contentment, satisfaction, and joy
Fear	Triggers a fight or flight response
Anger	Feelings of hostility and frustration
Surprise	It is a transitory emotional state expressing either of positive or negative impression
Disgust	A strong emotion of repulsion

4. Result and Discussion

The result of the emotional analysis is presented in this section. Considering the response rate of 63.46% presented in Table 2, data acquired for this study is *excellent* for adequate analysis and reporting on the subject matter, as it complies with Mugenda and Mugenda generalization theory [25]. Therefore, conclusion on the study would be valid for generalization. The multi-class emotional status for each opinion as expressed by the octogenarians is returned as the experimental result of the analysis. This is based on the opinions of 63.46% of respondents which almost evenly represents the male and female gender, with 81.81% within the age bracket of 80 – 85 years. A 48.48% of the respondents possess Bachelors degree with 33.33% having between one to three years user-experience of mobile health applications. The box plot detailing the spontaneous mood of the Octogenarians on mobile health concerns is as presented in

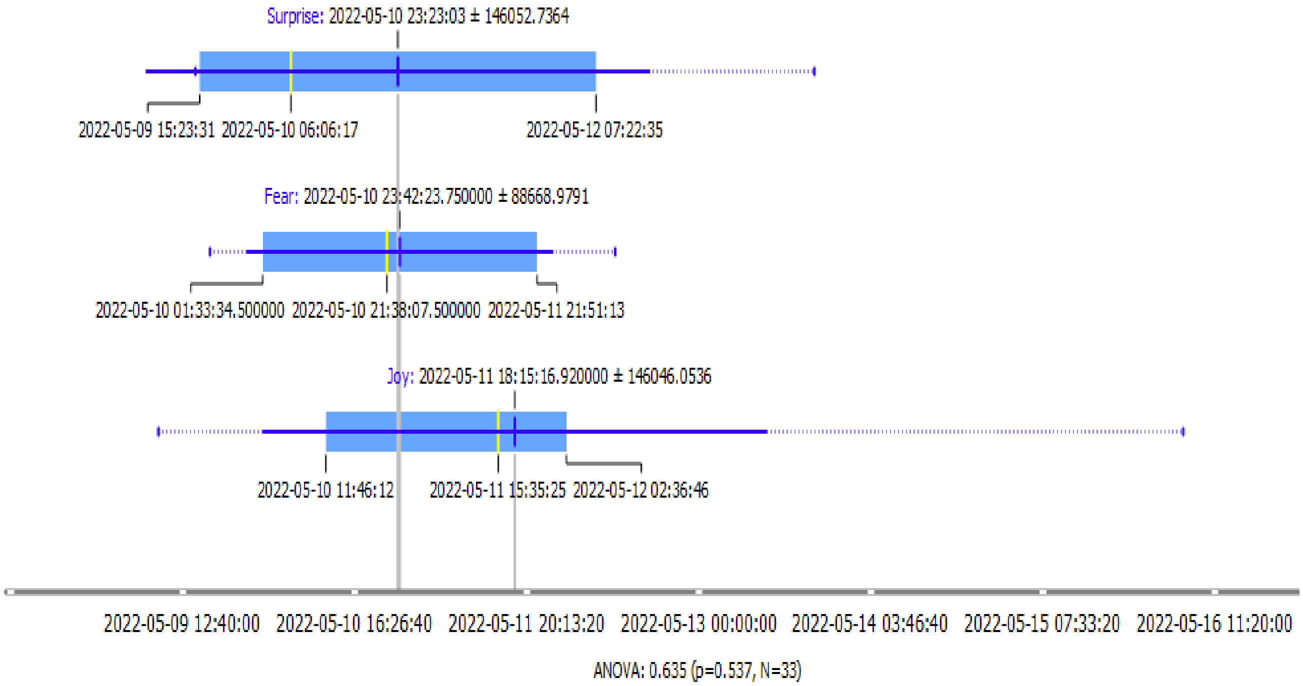

Figure *2*. It is evident from the analysis that only three mood states of *Surprise, Fear, and Joy* are observed from the textual opinions. Opinions were captured and retrieved in real time between 9th and 16th May, 2022 starting from 12:40:00 pm till 11:20:00 am. The mood state of *Surprise* was first identified on the box plot interquartile range on the 9th of May, and lasted till the 12th of May at about 07:22:25 pm as the most prominently displayed mood by the Octogenarians during the course of the real time data acquisition. The Octogenarians started expressing *Fear* mood over their M-Health applications at about 01:33:34 am of 10th May, 2022 which lasted till 21:51:13 pm of 11th May, 2022. The *Joyous* mood was observed within the acquired corpus on 10th May at about 11:46:12 am till 02:36:46 am of 12th May, 2022. Comparing the Mean of the mood classes, the Analysis of Variance (ANOVA) returns a 0.635 as evident on the Figure 2 with the value of *p* at *0.537* out of the total population of N=33. The low *p-value* is an indication of a strong proof against the null hypothesis thereby establishing the fact that there exist a statistical relationship of high significance in the set of opinions expressed by the Octogenarians. It can further be observed from Figure 3 that 4 (12.12%) Octogenarians exhibited the *Fear* mood consistently within the aforementioned timeline while another 4 (12.12%) exhibited the *Surprise* mood throughout the timeline of the experimentation. The *Joy* mood remained consistent throughout the experimentation timeline for 25 (75.75%) of the Octogenarian respondents. Experimental result returned *Surprise* as the most prominent emotion exhibited during the timeline which is a transitional emotional state that could either depict a positive or negative impression.

Table 2: Distribution of respondents across varying parameters

Questionnaire administration	**Frequency**	**Percentage**
Number Octogenarians who received Google form link	52	100%

Total number of responses	33	63.46%
Total number of decline	19	36.53%
Gender distribution of respondents	Male: 16 Female: 17	Male: 48.48% Female: 51.51%
Age bracket of respondents		
80 – 85 years	27	81.81%
86-89 years	6	18.18%
Educational level of respondents		
Postgraduate	9	27.27%
Bachelor’s degree	16	48.48%
Others	8	24.24%
Year of experience with e-Health		
Up to 1 year	9	27.27%
1-3 years	11	33.33%
4-6 years	8	24.24%
7-10 years	5	15.15%
Over 10 years	0	-
e-Health software adopted		
Omomi	8	24.24%
Hudibia	4	12.12%
Find-A-Med	12	36.36%
25 Doctors	3	9.09%
Kangpe	6	18.18%

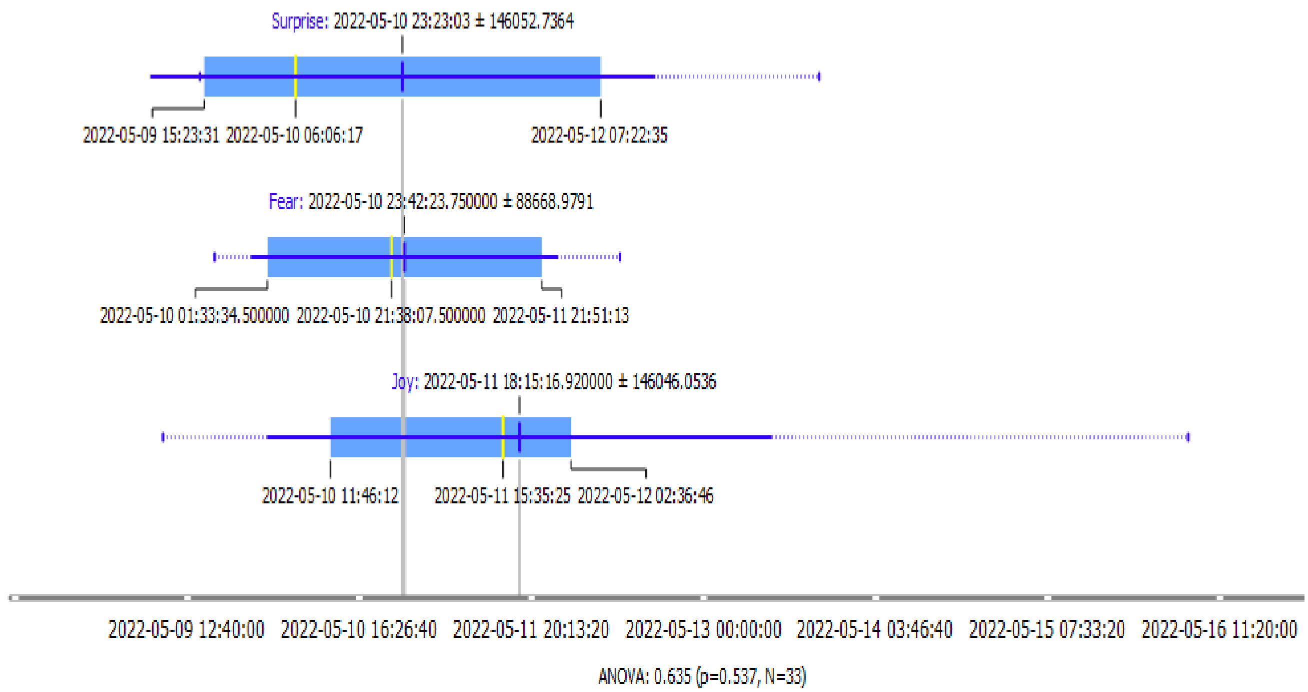

Figure 2: Box plot showing the Ekman's emotional moods of Octogenarian respondents

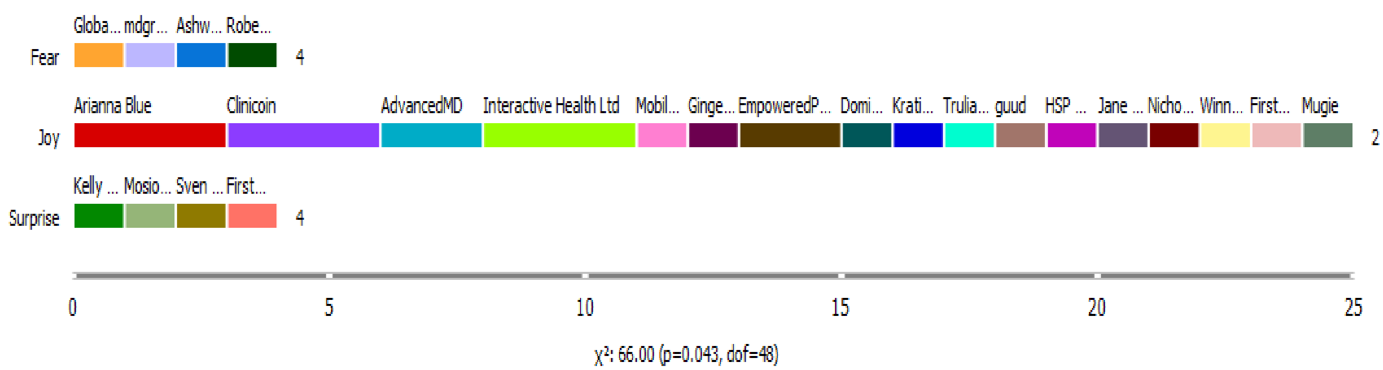

Figure 3: Distribution of Octogenarian mood swings across the Ekman's classification model

5. Conclusion and Recommendation

This study employed a Google form questionnaire approach to acquire a time-stamped opinions of Octogenarians on the use of mobile health applications for healthcare delivery services. For the period of the survey, respondents constantly fill out their opinions on new developments and impressions on ease of use, affordability, perceived usefulness, etc. The opinions are subjected to Paul Ekman's theory of emotions to identify various emotional states as contained in the real time corpus. Experimental result returned *Surprise* as the most dominant emotion, with transitions between it, *Fear*, and *Joy*. The *Surprise* emotional mood lasted between 15:23:31 pm of 9th May, 2020 till 7:22:35 am of 12th May, 2022. The *Joy* emotion was short-lived between 11:46:12 am of 10th May, 2022 till 15:35:25 pm of 12th May, 2022. In the final analysis, only four respondents each were constantly exhibiting the *Fear* and *Surprise* emotions throughout the timeline, while twenty-five respondents were predominantly *Joyful* with the use of their M-Health application for healthcare delivery. This discoveries could aid the improvement of public health policies for universal health coverage intentions and as well as help to understand the prominence of emotional spontaneity in opinion mining analytics through sentiment analysis. Future studies could model a machine learning model that will identify the demographics of respondents based on their time-stamped emotional mood classification.

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