

Analyzing User Expectations and Usability Alignment in Augmented Reality Using Principal Component Analysis and Regression

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Abstract: Understanding visitor expectations is crucial for developing user-centered Augmented Reality (AR) applications for cultural heritage. This study investigates the relationship between visitor expectations and perceived usability of the Mooi Indie AR painting application using Principal Component Analysis (PCA) and regression analysis. Initial data were collected from 78 participants, and PCA reduced eight expectation variables into three principal components, which explained 65.73% of the total variance. PCA reduced these into three main components: 1) Perceived Experience Value, 2) Engagement and Cultural Familiarity, and 3) Technology Adoption Intention. Regression analysis was then conducted as an exploratory approach to examine the relationship between the extracted expectation dimensions and perceived usability. Results indicate that the AR application generally met or exceeded visitors' initial expectations, demonstrating its potential to enhance user engagement in cultural heritage exhibitions. The proposed analytical framework provides practical insights for identifying key expectation dimensions to support the design of more effective, user-centered AR applications.

Keywords: User Expectation, User Experience, Usability, Principal Component Analysis, Augmented Reality

Introduction

In software quality assurance, usability is a part of user experience that is one of the essential key attributes (Ferreira and Canedo, 2020). The user experience must meet user expectations to ensure user satisfaction and usability (Khalane and Tanner, 2013; Wang and Liu, 2023). User satisfaction and behavioral intentions that start from reasonable expectations will also result in a good user experience (Wang and Zhou, 2023). The enjoyment expected by users is supposed to have a long-term effect on software products, including recommending products to others (Kujala and Miron-Shatz, 2015). One of the main challenges in software product development is the inability to meet or even understand user expectations (Fernandez et al., 2011). Therefore, developers then use a user-centered approach so there is no gap between what is needed and what is provided by the software product (Jake-Schoffman and McVay, 2021). User involvement in the software project development process also avoids internal assumptions,

where developers consider intuitive features may be complicated or irrelevant to users. Unintuitive interfaces, slow response times, and products that are difficult to use will frustrate users and then leave them (Wahyuningrum et al., 2019). The dynamics of users exacerbate this challenge, which continues to change over time and in the context of use. Without an adaptive and data-driven expectation modelling process, products will be trapped in a reactive, not strategic, development cycle. Modeling user expectations will help developers understand user needs based on quantitative data (Maqbool and Herold, 2024; Naswir et al., 2019). By understanding user expectations and needs more accurately and compiling the right features, the chances of a product being rejected or failing in the market can be reduced (Khoo et al., 2020; Wahyuningrum et al., 2025; Zschech et al., 2020).

User experience in Augmented Reality (AR) software products generally refers to the psychological aspects, where the product meets or exceeds user expectations. The development of AR technology has opened new opportunities to create more interactive,

immersive, and enjoyable experiences. One example is the implementation of AR technology through interactive filters on social media, which can provide a high level of entertainment and interactivity (Ibáñez-Sánchez et al., 2022). The use of AR filters in Instagram stories is considered effective in increasing awareness and supporting experiential learning processes through interactivity and enjoyment (Sukmawati et al., 2022). In the context of education and aesthetic experiences, AR technology can provide a more immersive experience, enabling users to interact directly with virtual environments. Research by Zhou and Li (2024) shows that the use of AR in digital exhibitions can significantly enhance the aesthetic and user experience. Meanwhile, in museum environments, AR technology is used to enhance the visit experience by presenting additional information, enabling interactive navigation, and fostering more engaging collaborative experiences for visitors (Lupascu et al., 2021). User expectations and user experience when using AR during museum visits will increase visitors' satisfaction by creating an informative and engaging learning experience (Nor and Razak, 2021). Museums are increasingly adopting Augmented Reality (AR) to enrich cultural heritage interpretation by integrating digital content with physical artifacts, thereby creating more interactive and engaging visitor experiences. Recent studies have shifted their focus from technology implementation toward understanding visitors' perceptions, interactions, and overall experiences with AR applications in cultural heritage settings (Fontana, 2025; Kukreja et al., 2022). Although visitor experience is recognized as a multidimensional construct, most previous studies have focused on post-use evaluation rather than examining visitors' expectations prior to usability assessment (Zhang et al., 2024). Based on this research, it can be concluded that AR functions not only as a visualization technology but also as a medium that enhances user experience, aesthetics, interactivity, and user engagement. Therefore, the user experience must always align with user expectations so that digital products are useful and easy to use.

To achieve a good user experience, it is essential to set realistic user expectations. The approach to collecting user needs and expectations generally uses the interview method (Bahareh, 2015; King et al., 2023; Nugraha and Fatwanto, 2021) or survey (Adellia and Prasetyo, 2016; Singh and Malik, 2016). The interview approach can provide in depth, flexible, and responsive insights, but is time-consuming, costly, highly subjective, and difficult to quantify. Meanwhile, the survey's characteristics include its ability to reach a large population and describe broad user-based preferences for software products, making it often used in the early stages of understanding potential users. Using a closed questionnaire to describe user expectations, the survey method is considered appropriate for statistical analysis (Arce et al., 2022; Sadowska, 2015). Respondent data on

user expectations were collected using a survey method using a questionnaire tool. In this research, we decomposed the raw expectation data using Principal Component Analysis (PCA) to reduce high-dimensional data (Alkhayrat et al., 2020). PCA is a standard mathematical model for improving interpretability without losing much information by creating new covariates (Beattie and Esmonde-White, 2012; Hasan and Abdulazeez, 2021). The results of variable reduction using PCA were used for regression analysis to predict user experience. The regression model established the relationship between user experience, as the dependent variable (Y), and user expectation, as the independent variable (X). Regression analysis extracted sample expectation data and identified significant factors that affected the user experience, using the dependent variable (Ayalew, 2020; Chen et al., 2020). This study combined PCA and regression models to create a new integrated model that reduced dimensionality and identified factors underlying user expectations. Therefore, Principal Component Analysis (PCA) was employed to identify the underlying dimensions of visitor expectations by reducing redundancy among correlated variables, while regression analysis was subsequently used to explore the relationship between these expectation dimensions and perceived usability (Howard and Henderson, 2023). The findings are expected to support the development of user-centered AR applications that better align with visitor expectations in cultural heritage environments. This study explored the integration of PCA and regression with AR product experiments in art exhibitions, classroom practicals conducted by students, and experiments led by lecturers and art practitioners in Indonesia and Malaysia. The main purpose of this AR product was to offer unique experiences for museum or art gallery visitors, thereby attracting tourists interested in art and culture. Initial research on AR has been applied to traditional paintings by the Sokaraja artist in Central Java, Indonesia, with the theme Mooi Indie (a theme featuring natural scenery, such as mountains and rivers) (Wahyuningrum et al., 2025). The results showed that groups who had used AR had better user experience scores than those who had not used AR. This study still needs to be improved in modeling a user experience prediction if user expectation data are known.

Methods

This research method consisted of three main stages designed to systematically analyze and predict user expectations. The first stage involved collecting raw expectation data from respondents through questionnaires instruments. In this stage, various variables related to user expectations were collected to obtain comprehensive information regarding users' perceptions, preferences, and anticipated experiences with the system or media being evaluated. The collected data represented an initial expectation dataset that still contained many interrelated variables. The second stage focused on simplifying and

reducing the complexity of the initial expectation data using a Principal Component Analysis (PCA) approach. PCA was applied to identify the most significant components of the original variables by transforming correlated variables into a smaller number of principal components while retaining most of the essential information contained in the dataset. This dimensionality reduction process helped minimize redundancy, improved data interpretation, and identified dominant factors influencing user expectations. The third stage used the reduced components generated by PCA as input variables for a regression analysis to predict user expectations. The regression analysis examined the relationship between the principal components and the targeted outcomes, enabling the development of a predictive model with more efficient and reliable variables. Through this approach, this study aims to gain a more accurate understanding of the factors influencing user expectations and to generate predictive models that can support future decision-making and system development. Fig. 1 illustrates the overall stages of the investigation process.

Raw User Expectation Data

The survey design was created based on the needs and expectations of users of the AR application for Mooi Indie Painting. We collected data from 78 respondents aged around 18-35 years who had visited an art exhibition using convenience sampling. Respondents were recruited online via a Google Form through the art and design class group and the lecturer group. Although the sample size was relatively modest, this study was designed as an exploratory investigation to capture raw user expectation data from actual visitors who experienced the AR system (Tullis and Albert, 2013). Fig. 2 presents the user scenario for AR painting application.

Fig. 2 presents the user scenario of the AR painting application. The visitor uses their phone to open the AR application and use the camera to capture the painting, enabling the application to recognize the artwork and overlay augmented reality content, including animations, historical information, and audio narration.

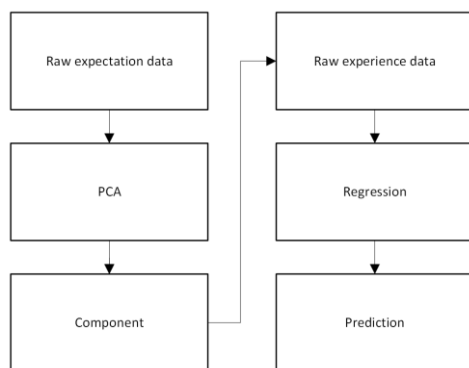


Fig. 1: Research method of integration PCA and regression

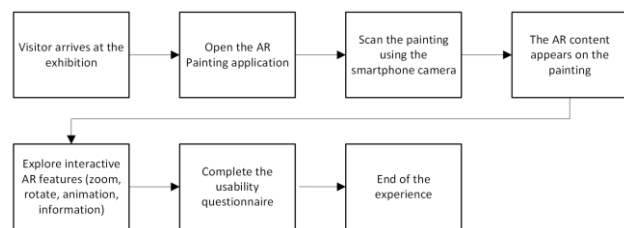


Fig. 2: User scenario illustrating how visitors interact with the AR painting application during the museum experience

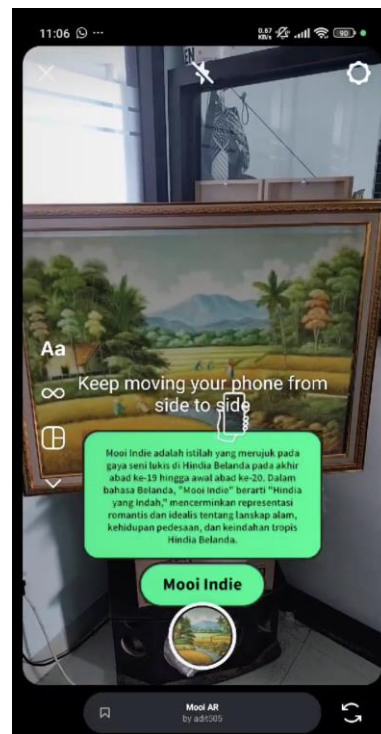


Fig. 3: An augmented reality interface displaying contextual information and animated movement of clouds, people, and other objects for mooi indie paintings

Visitors interact with these digital elements to explore the artwork in greater depth before completing the evaluation questionnaire. This scenario demonstrates the practical use of the AR application within the museum environment and provides the context for collecting user expectations and usability data.

The mobile AR app's user interface presents contextual information about Mooi Indie's paintings (Fig. 3). When the camera recognizes the artwork, the system displays a descriptive information panel explaining its historical background in Indonesian. Furthermore, objects captured by the camera are animated, bringing the painting to life. The interface also provides navigation controls and visual guides to help users maintain proper camera alignment during artwork recognition, enabling an interactive and informative museum experience.

Before performing Principal Component Analysis (PCA), the suitability of the dataset was evaluated using the Kaiser Meyer Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. The KMO statistic was used to assess whether the correlations among variables were adequate for factor extraction, while Bartlett's Test examined whether the correlation matrix significantly differed from an identity matrix. A KMO value greater than 0.60 and a significant Bartlett's Test ($p < 0.05$) were considered evidence that the data were appropriate for PCA. The questionnaire consisted of 14 questions and was summarized in 14 variables, as shown in Table 1. We excluded variables X_{1-2} and X_{12-14} from the PCA calculation because the data in these variables were on a nominal scale.

Principal Component Analysis

Principal Component Analysis (PCA) is a dimensionality reduction technique that transforms a set of correlated variables into a smaller number of orthogonal (uncorrelated) components while preserving as much of the original data variation as possible. The PCA procedure consists of several sequential steps. First, the dataset is standardized to ensure that all variables are measured on a comparable scale. Next, the covariance matrix is calculated, followed by the eigenvalue and eigenvector estimation (Kang et al., 2020; Li et al., 2020). The eigenvalues and corresponding eigenvectors are then ranked in descending order, after which the top k principal components are selected to construct the eigenvector matrix. Finally, the original data are projected onto the selected principal components. During the standardization process, the mean and standard deviation of each feature are computed as shown in Eq. (1):

$$x_{new} = \frac{x - \mu}{\sigma} \quad (1)$$

Where x represents the observed value, μ denotes the mean, and σ refers to the standard deviation. Once the mean and standard deviation have been determined, the covariance matrix is computed. Covariance is a statistical measure used to evaluate the strength and direction of the linear relationship between two variables. The construction of the covariance matrix involves calculating both the variance (Eq. (2)) and the covariance (Eq. (3)):

$$Var(x) = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1} \quad (2)$$

$$Cov(x, y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n-1} \quad (3)$$

Where x denotes the observed value; μ represents the mean; n is number of variables. The results of the calculations on variance and covariance are then applied to the covariance matrix, following the rules outlined in the covmat matrix (Eq. (4)):

$$covmat = \begin{pmatrix} var(x) & cov(x, y) \\ cov(y, x) & var(y) \end{pmatrix} \quad (4)$$

Next, the eigenvalues and eigenvectors of the covariance matrix are computed. The eigenvalues indicate the amount of variance explained by each principal component, whereas the corresponding eigenvectors define the directions of the new feature space. The eigenvectors are obtained by solving the characteristic equation $Av = \lambda v$, where A is the covariance matrix, v is the eigenvector, and λ is the associated eigenvalue (Eq. (5)):

$$Av = \lambda v = 0; (A - \lambda I)v = 0 \quad (5)$$

Where v represents a non-zero eigenvector. The equation has a nontrivial solution when the condition in Eq. (6) is met:

Table 1: Research variables of user expectation

Variables	Description	Value
X_1	Age	1: Under 18 y.o; 2: 18-25 y.o; 3: 26-25 y.o
X_2	Gender	1: Male; 2: Female
X_3	Social media sharing	0: No; 1: Yes
X_4	Willingness to install	0: No; 1: Yes
X_5	Willingness to pay	0: Free; 1: Under 1 USD; 2: 1-5 USD; 3: Upper 5 USD
X_6	Confidence boost	1: Not at all confident; 2: Slightly confident; 3: Neutral; 4: Confident; 5: Very confident
X_7	Interest visit	1: Strongly disagree; 2: Disagree; 3: Neutral; 4: Agree; 5: Strongly agree
X_8	Visit frequency	1: Seldom (once a year); 2: Sometimes (2-4 time a year); 3: Often (more than 5 times a year)
X_9	Familiarity AR	1: Not at all familiar; 2: Slightly familiar; 3: Neutral; 4: Familiar; 5: Extremely familiar
X_{10}	Familiarity Mooi Indie Painting	1: Not at all familiar; 2: Slightly familiar; 3: Neutral; 4: Familiar; 5: Extremely familiar
X_{11}	Importance AR feature	1: Not at all important; 2: Slightly important; 3: Neutral; 4: Important; 5: Extremely important
X_{12}	Expectations AR feature	1: Added information; 2: Artistic information; 3: Animation; 4: User interaction; 5: Sound and music activation
X_{13}	Preferred AR	1: AR glasses (Google glass, hololens); 2: smartphone (IOS, android); 3: tablet
X_{14}	Most valuable AR feature	1: 3D visual; 2: AR effects; 3: audio guide; 4: gamification

$$\det(A - \lambda I) = 0 \quad (6)$$

The first two principal eigenvectors, corresponding to the largest eigenvalues, were selected because they captured the majority of the data variance. These eigenvectors were then used to project the original dataset into a two-dimensional feature space using $AV_k = B$.

Regression

After obtaining the reduced variables from the PCA process, we then used a questionnaire with the same variables as the PCA results to gather user assessments of the final AR application product. Linear regression is a statistical method to study the relationship between two or more variables (Kong et al., 2020). This method can predict the value of the user experience, denoted as the dependent variable (Y), based on the value of the user expectation as the independent variable (X). Eq. (7) shows the general form of the multiple linear regression formula:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \epsilon \quad (7)$$

To determine the regression equation, the best regression line must be found by minimizing the sum of the squares of the differences between the observed Y values and the predicted Y values Eq. (8) and Eq. (9):

$$\beta_1 = \frac{(\sum x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \quad (8)$$

$$\beta_0 = \bar{y} - \beta_1 \bar{x} \quad (9)$$

The value of Y is determined by a baseline value (β_0), plus the combined effects of several independent variables ($\beta_i X_i$), along with some random error (ϵ).

Results and Discussion

This study employs PCA and linear regression as an exploratory analytical framework to identify the underlying dimensions of visitor expectations and examine their relationship with perceived usability. The objective is not to develop or validate a causal model, but to provide an initial understanding of expectation structures that can support the user-centered design of AR applications for cultural heritage. The following explanations are the results and discussion of the PCA and linear regression approach.

Kaiser Meyer Olkin (KMO) and Bartlett's Test

To reduce the dimensionality of the user expectation variables and identify the underlying latent constructs, Principal Component Analysis (PCA) was performed. Before conducting PCA, the suitability of the dataset was assessed using the Kaiser Meyer Olkin (KMO) Measure of Sampling Adequacy, Bartlett's Test of Sphericity, and the Anti-image Correlation Matrix. During the preliminary analysis, the variable Willingness to Pay (X_5)

produced a Measure of Sampling Adequacy (MSA) value of 0.281, which was substantially below the recommended threshold of 0.50. This result indicates that the variable shared insufficient common variance with the remaining variables and was therefore unsuitable for inclusion in the PCA. Following the recommendation of Hair et al. (2019), variables with MSA values below 0.50 should be excluded to improve the stability and interpretability of the extracted components. Consequently, X_5 was removed, and the PCA was repeated using the remaining eight variables.

Table 2 presents the results of the KMO and Bartlett's Test after the removal of X_5 . The revised analysis yielded a KMO value of 0.755, indicating satisfactory sampling adequacy. Furthermore, Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 153.402$, $df = 28$, $p < 0.001$), confirming that the correlation matrix differed significantly from an identity matrix. These findings indicate that the remaining variables possessed sufficient intercorrelations to justify the application of PCA.

The sampling adequacy of the retained variables was subsequently confirmed through the Anti-image Correlation Matrix. As summarized in Table 3, all variables obtained MSA values above the recommended threshold of 0.50, ranging from 0.655 to 0.824. These findings indicate that each variable met the assumptions required for PCA and was therefore retained for subsequent component extraction.

Principal Component Analysis

The first stage was to reduce the variable of user expectation. Eq. (1)-(5) were then used step by step to generate the PCA output, calculated using statistical software. Based on the calculation results, the total variance explained was obtained. This condition referred to the extent to which the principal components produced by PCA could explain the variation (or information) in the raw user expectation data.

Table 2: KMO and bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.755
Bartlett's Test of Sphericity	Approx. Chi-Square
	df
	28
	p
	<0.001

Table 3: Measures of Sampling Adequacy (MSA)

Variable	MSA
Social Media Sharing	0.761
Willingness to Install	0.824
Confidence Boost	0.713
Interest Visit	0.751
Visit Frequency Art Gallery	0.794
Familiarity with AR	0.655
Familiarity with Mooi Indie	0.818
Importance of AR Features	0.774

Table 4: Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.035	37.933	37.933	3.035	37.933	37.933
2	1.222	15.272	53.205	1.222	15.272	53.205
3	1.002	12.529	65.734	1.002	12.529	65.734
4	0.800	10.000	75.734			
5	0.698	8.723	84.457			
6	0.597	7.458	91.916			
7	0.389	4.868	96.784			
8	0.257	3.216	100.000			

*Extraction method: Principal component analysis

Table 4 shows the variance results of the initial eigenvalues in the data, which shows the number of variables.

The extraction sums of squared loading columns show the number of variations or the number of factors that can be formed. As shown in Table 4, there are three-factor variations, namely 3.035, 1.222, and 1.002. Based on the output from Table 4, three components can be formed from the eight variables analysed, where the eigenvalues of each are greater than 1. Component 1 explains 37.933% of the variation, component 2 explains 15.272% of the variation, and component 3 explains 12.529% of the variation. Furthermore, the number of components in PCA can be determined visually through the Scree plot. A scree plot helps determine how many principal components should be retained in the analysis. Scree plots are very useful in making decisions related to data dimension reduction. The scree plot graph is shown in Fig. 4.

As seen in Fig. 4, the Scree plot, it can be observed that the eigenvalues for components 1, 2, and 3 are greater than 1, indicating that these components can be formed into three main components. Visualizing the main components through a scree plot helps to intuitively understand the data structure, showing observations grouped based on their component scores. Communalities indicate the proportion of variance of each variable explained by the three components.

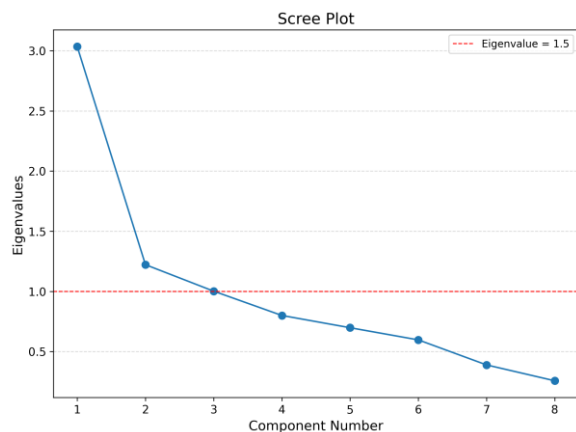


Fig. 4: Scree Plot

Communalities indicate the proportion of variance in each original variable that can be explained by the principal components, namely the three components. A good communality value is generally above 0.5. So, from Table 5 we get the variable with the highest communality value, namely X_6 , Confidence Boost (0.806); X_{11} , Importance AR Feature (0.710), X_7 , Interest Visit (0.755), and the lowest contribution is X_{10} (Familiarity Mooi Indie (0.530)).

Next, new variables were obtained by linearly combining the initial variables. These components were ranked by importance. To improve the interpretability of the extracted components, Varimax rotation with Kaiser normalization was performed. Based on the loading values in Table 6, the three main components formed can be interpreted as follows.

Component 1: Perceived Experience Value

The first component is dominated by the variables Confidence Boost (0.892), Interest to Visit (0.819), and Importance of AR Feature (0.756). The high loading value indicates that this component represents the dimension of user confidence and interest in AR, especially in the context of the cultural experience offered. These variables collectively capture the extent to which AR experiences strengthen visitors' confidence, increase their intention to visit, and enhance the perceived usefulness of AR functionalities.

Component 2: Engagement and Cultural Familiarity

The second principal component was primarily characterized by Visit Frequency at Art Galleries (0.821) and Familiarity with Mooi Indie (0.678). These variables represent visitors' prior exposure to museum environments and their knowledge of the artworks on display. Accordingly, this component was interpreted as Engagement and Cultural Familiarity.

Component 3: Technological Adoption Intention

The third principal component comprised Social Media Sharing (0.695), Willingness to Install (0.570), and Familiarity with AR (-0.584).

Table 5: Communalities

Variables	Description	Initial	Extraction
X_3	Social Media Sharing	1.000	0.549
X_4	Willingness to Install	1.000	0.537
X_6	Confidence Boost	1.000	0.806
X_7	Interest Visit	1.000	0.755
X_8	Visit Frequency Art Gallery	1.000	0.704
X_9	Familiarity AR	1.000	0.668
X_{10}	Familiarity Mooi Indie	1.000	0.530
X_{11}	Importance AR Feature	1.000	0.710

*Extraction Method: Principal component analysis

Table 6: Rotated component matrix

Variables	Description	Component 1	Component 2	Component 3
X_3	Social Media Sharing	0.066	0.248	0.695
X_4	Willingness to Install	0.453	0.077	0.570
X_6	Confidence Boost	0.892	0.050	0.085
X_7	Interest Visit	0.819	0.206	0.205
X_8	Visit Frequency Art Gallery	0.057	0.821	0.161
X_9	Familiarity AR	0.312	0.480	-0.584
X_{10}	Familiarity Mooi Indie	0.259	0.678	0.061
X_{11}	Importance AR Feature	0.756	0.340	-0.151

Extraction Method: Principal component analysis

Rotation Method: Varimax with Kaiser Normalization.a

a. Rotation converged in 6 iterations

Although the loading for Familiarity with AR was negative, its absolute value remained substantial, indicating that the variable contributed meaningfully to the component but in the opposite direction. This component reflects visitors' readiness to adopt and interact with digital technologies and is therefore interpreted as Technology Adoption Intention. PCA analysis successfully transformed eight variables into three principal components, which explained over 65.73% of the total variance. This result indicates that the extracted components retained a substantial proportion of the information contained in the original variables while effectively reducing dimensionality. The three-component solution captures the principal dimensions of visitors' expectations toward the AR painting application for Mooi Indie artworks, providing a simplified yet representative structure for subsequent analysis and interpretation. Given the multidimensional nature of behavioral and user experience data, a cumulative explained variance exceeding 60% is generally regarded as satisfactory for exploratory research (Howard and Henderson, 2023; Schreiber, 2021; Sigudla and Maritz, 2023).

Linear Regression

After successfully reducing user expectation data, we conducted another survey with 41 respondents to assess the application based on their experience using three component attributes, 1) Perceived Experience Value, 2) Engagement and Cultural Familiarity, 3) Technological

Adoption Intention. Then, we analysed to see whether the AR application on Mooi Indie paintings had met user expectations. Thus, the respondents were divided into two groups: Group 1 (n = 78), who completed the user expectation questionnaire, and Group 2 (n = 41), who completed the user experience questionnaire after using the product. The respondents were from Indonesia and Malaysia. The sample consisted of one respondent under 18 years old, 30 respondents aged 18-25, and 20 respondents aged 26-35, as shown in Fig. 5.

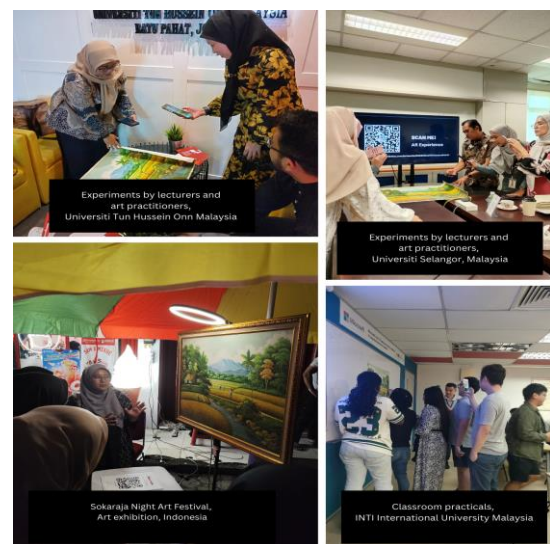


Fig. 5: AR Mooi Indie Application Testing with real user

Table 7: Aggregation Output per Attribute

Attribute	E_{mean}	R_{mean}	Gap(R-E)
Interest and confidence in AR	0.6214	0.7938	+0.1724
Readiness for technology implementation	0.5257	0.7438	+0.2181
Technological familiarity and perceived value	0.3920	0.7813	+0.3893

Fig. 3 illustrates the evaluation of the proposed AR painting application across several real-world settings, including public exhibitions, cultural festivals, and university environments in Indonesia and Malaysia. These diverse testing contexts involved participants with different educational backgrounds, levels of familiarity with AR technology, and interaction environments. Although contextual differences may have influenced individual perceptions of usability, conducting the evaluation in multiple real-world settings enhances the ecological validity of the findings by demonstrating that the application can be used across different cultural and educational contexts rather than under a single controlled laboratory condition. Due to using different respondents, the prediction was made at the aggregate level, with the average expectation of each attribute E_{mean} as the independent variable and user experience (R_{mean}) as the dependent variable so that the model is as Eq. (10):

$$\text{Experience} = \beta_0 + \beta_1 \text{Expectation}_i + \varepsilon_i \quad (10)$$

The results obtained from the Aggregation output per attribute can be seen in Table 7. Variable E_{mean} , or expectation mean, is the respondent's expectation score for the AR application in painting. Meanwhile, R_{mean} is the average actual assessment score (experience of the AR painting application product performance) from different respondent groups for the same attribute. The difference between R_{mean} and E_{mean} is interpreted as: If the gap is more than 0, the product has exceeded expectations; otherwise, the product has not met user expectations. Thus, we can interpret which attributes require priority improvement (negative gap) and whether there is a systematic pattern between expectations and realization. Technological familiarity and perceived value are seen to exceed expectations the most, while interest and confidence in AR have the lowest expectations. However, the positive sign indicates that the reality on the ground has exceeded user expectations.

To create a regression model, we first calculated the average of $\bar{X}$ and $\bar{Y}$ (see Eq. (11) and Eq. (12)):

$$\bar{X} = \frac{0.6214 + 0.5257 + 0.3920}{3} \approx 0.5130 \quad (11)$$

$$\bar{Y} = \frac{0.7938 + 0.7438 + 0.7813}{3} \approx 0.7729 \quad (12)$$

Meanwhile, the slope β_1 was calculated using the Eq. 7 as follows:

Meanwhile, the slope β_1 was calculated using the Eq. (7) as follows:

$$\text{For } X_1 = 0.6214, Y_1 = 0.7938$$

$$(X_1 - \bar{X}) \times (Y_1 - \bar{Y}) \approx (0.1084) \times (0.0209) \approx 0.00227; (X_1 - \bar{X})^2 = 0.01175$$

$$\text{For } X_2 = 0.5257, Y_2 = 0.7438$$

$$(X_2 - \bar{X}) \times (Y_2 - \bar{Y}) \approx (0.0127) \times (-0.0291) \approx -0.00037; (X_2 - \bar{X})^2 = 0.00016$$

$$\text{For } X_3 = 0.3920, Y_3 = 0.7813$$

$$(X_3 - \bar{X}) \times (Y_3 - \bar{Y}) \approx (-0.1210) \times (0.0084) \approx -0.00101; (X_3 - \bar{X})^2 = 0.01464$$

Slope β_1 and intercept (β_0) calculation can be seen as follows Eq. (13), (14):

$$\beta_1 = \frac{0.00089}{0.02655} \approx 0.0336 \quad (13)$$

$$\beta_0 = 0.7729 - (0.0336)(0.5130) \approx 0.7557 \quad (14)$$

So that a linear regression equation can be written for user expectations that influence user experience $\bar{Y} = 0.7557 + 0.0336X$. The interpretation of the model is that every 0.1 increase in mean of expectation increases mean of experience by approximately 0.00336 points. While this value is not highly significant, it is a reasonable finding given the data set of only three points. This model indicates a positive relationship between X and Y , where an increase in X slightly increases the predicted value of Y . To clarify the findings, we present a scatterplot image of the Scatter Plot with Linear Regression in Fig. 6.

The graph in Fig. 6 shows a scatterplot of E_{mean} vs. R_{mean} , with the regression line (red). Each point represents one attribute: Interest and Confidence in AR, Readiness for Technology Implementation, and Technological Familiarity and Perceived Value.

The graph shows that although expectations vary, assessments are relatively high and do not differ significantly across attributes.

The integration of Principal Component Analysis (PCA) and regression analysis provides a structured analytical framework for understanding visitors' expectations toward the AR painting application.

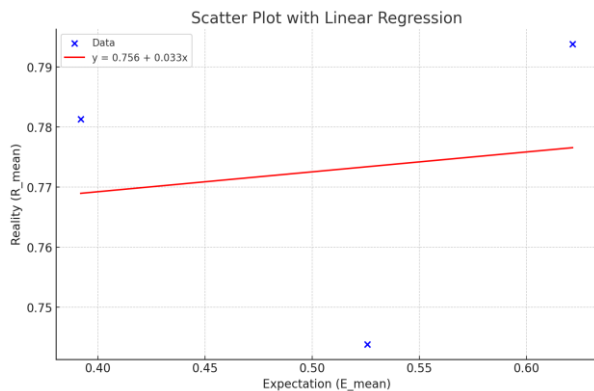


Fig. 6: Scatter plot with linear regression

PCA first reduces the complexity of the questionnaire by identifying a smaller number of latent dimensions from correlated expectation variables, thereby minimizing redundancy while preserving most of the original information. These extracted components are subsequently incorporated into the regression model to examine their influence on perceived usability. This sequential approach enables the study to move beyond describing individual questionnaire items by revealing the underlying expectation constructs and quantifying their contribution to users' perceptions of usability. Consequently, the findings offer more focused evidence for prioritizing design improvements in AR-based cultural heritage applications.

This analytical framework is consistent with previous studies that recommend dimensionality reduction techniques for handling correlated perceptual variables before predictive analysis. PCA has been widely adopted in Human-Computer Interaction and user experience research to identify meaningful latent constructs from user perception data, while regression analysis is commonly employed to evaluate the relationship between these constructs and usability outcomes. By combining these methods, the present study provides a more interpretable representation of visitors' expectations and a clearer understanding of which expectation dimensions are most strongly associated with perceived usability.

Conclusion

Based on the experimental evaluation of the Mooi Indie AR painting application, integrating Principal Component Analysis (PCA) and multiple linear regression provided a comprehensive understanding of visitors' expectations and their relationship with perceived usability. PCA successfully reduced the eight observed variables into three principal components, explaining 65.73% of the total variance and revealing the multidimensional nature of visitors' expectations. The regression analysis further showed

that these expectation dimensions explained only part of the variation in perceived usability, suggesting that additional factors beyond user expectations may also influence users' perceptions. These findings provide an initial empirical foundation for supporting user-centered design and the further development of AR applications for cultural heritage experiences. Future research should involve larger and more diverse samples from the same group of respondents to increase the generalizability of the findings. Other efforts could include incorporating additional explanatory variables related to user characteristics and technology acceptance, and using more sophisticated analytical approaches, such as Structural Equation Modeling (SEM) or Partial Least Squares-SEM (PLS-SEM), to better capture the complex relationships between visitor expectations, usability, and behavioral intentions.

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Author's Contributions

Tenia Wahyuningrum: Conceptualization, research design, methodology, supervision, write, review and edited.

Aditya Tama Isdiarto: Interface design, content development, visualization.

Robert Hendra Yudianto: User Experience evaluation, investigation, data collection, validation.

Rajermani Thinakaran: The conceptualization, data analysis, interpretation of results, and review of the manuscript prior to her passing.

Ethics

The authors are committed to maintaining the integrity and accuracy of this manuscript after publication. If any

ethical issues, errors, inaccuracies, or concerns related to the research are identified, the authors will take appropriate corrective actions, including providing clarifications, corrections, or retractions when necessary. All authors agree to cooperate with the publisher and editors in resolving any post-publication ethical matters in accordance with academic and research integrity standards.

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