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Online Measuring Feature for Batik Size Prediction using Mobile Device: A Potential Application for a Novelty Technology

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Abstract

The garment industry, particularly the batik sector, has experienced significant growth in Indonesia, coinciding with a rise in the number of online consumers who purchase batik products through e-Marketplaces. The observed upward trend in growth has seemingly presented certain obstacles, particularly in relation to product alignment and product information dissemination. Typically, batik entrepreneurs originate from Micro, Small, and Medium Enterprises (or MSMEs) that have not adhered to the global norms. As a consequence, there may be discrepancies in the sizes of batik products available for purchase. The issue of size discrepancies poses a source of discontent among online consumers seeking to purchase batik products via the e-Marketplace platform. This predicament also directly affects batik vendors, as they are compelled to resend batik items that align with the desired size specifications. An effective approach to address this issue involves employing a smartphone camera to anticipate body proportions, specifically the length and width of those engaged in online shopping. Subsequently, by the utilization of machine learning techniques, the optimal batik size can be determined. The UKURIN feature was created as a response to a specific requirement. However, it is essential to establish a methodology for investigating the elements that impact the intention to use this feature. This will enable developers to prioritize their feature development strategies more effectively. A total of 179 participants completed an online questionnaire, and subsequent analysis was conducted utilizing the Extended Technology Acceptance Model framework. All hypotheses utilized in this study were confirmed, with the exception of the hypothesis pertaining to Computer Self Efficacy, which did not demonstrate a statistically significant effect on Ease of Use Perception. The findings indicate that Usefulness Perception emerged as the most influential factor. Consequently, when designing and developing the novelty feature of UKURIN, it is imperative for designers and application developers to prioritize the benefits aspect.

Keywords: Batik; Computer Vision; Technology Acceptance Model; Social Influence; Computer Self Efficacy; Technological Facility

1. Introduction

Batik is an Indonesian traditional art that was designated a UNESCO Intangible Cultural Heritage in 2009. Since then, the national batik industry has witnessed rapid growth and has become the backbone of Indonesia's economy. Batik is also recognized as one of the Industry 4.0 priority industries. Moreover, in October 2021, the Ministry of Industry stated that in 2020 batik garments exports reached USD 532.7 million. It makes Batik as one of the backbone industries in Indonesia's economic growth. Batik industry has made a big contribution in creating job opportunities and has absorbed around 200 thousand workers dominated by small and medium size industries. Batik garments are used as clothing and diverse accessories, such as scarves, handbags, wallets, or face masks [1]. Most of the batik industry is inherited from the previous generation, and so this means that batik will be a sustainable business and a good opportunity for creating a new entrepreneur. Supported by e-commerce or e-marketplace, the promotion of batik has become easier and can reach out worldwide [2].

Indonesia encountered e-commerce in the 2000s and e-Marketplace in 2010. At first, Indonesian people were afraid to shop using e-Commerce or e-Marketplace because they feared the package, or the payment was not received or passed through. But since the security and payment system upgrades, people tend to shop by e-Marketplace frequently. By the first quartal of 2023, Shopee is the most frequently visited e-Marketplace in Indonesia, with an average number of visitors of 158 million as seen in Figure 1. Tokopedia became the second with 117 million average visitors. The trend is roses on public holidays and special dates, like Ramadan or Christmas. The government believes that e-Commerce and e-Marketplace will also help Indonesia's economic growth. One of Indonesia's largest national batik producers asserts that they adhere to higher standards than the country's general standards because their market share is not only national or regional in Southeast Asia but also global. With the increasing use of e-Commerce and online trading, however, people who purchase and sell batik through e-Marketplaces are frequently dissatisfied because the size of batik in Indonesia is not standard.

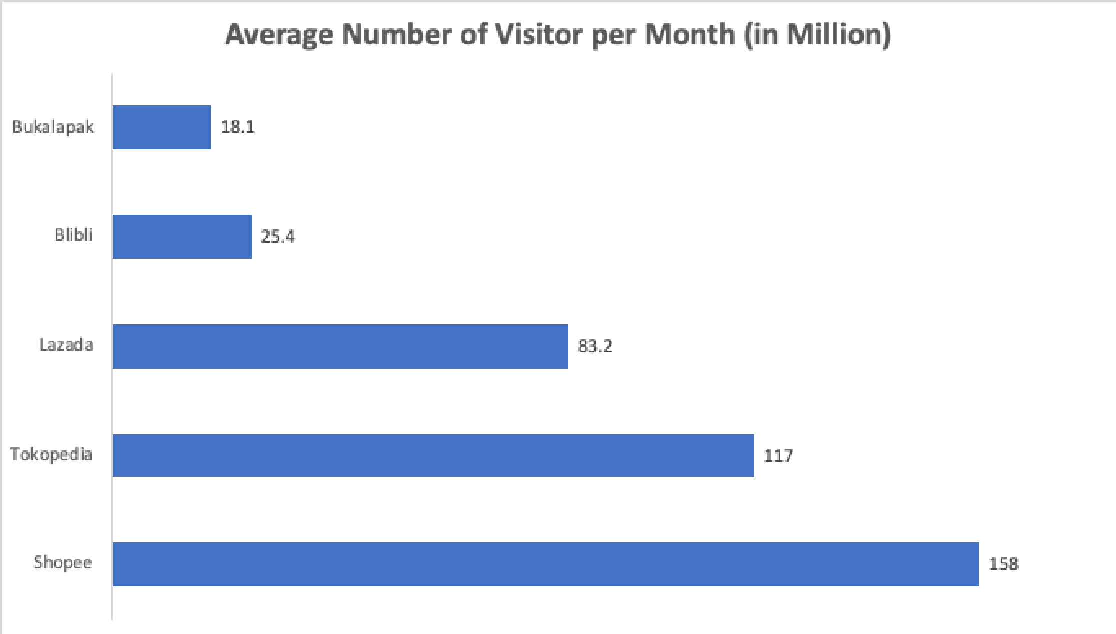

Figure. 1. The most frequently visited e-Marketplace in Indonesia
(Source: https://databoks.katadata.co.id)

Many factors, like regional or cultural aesthetics, body shapes, and clothing style, influence Indonesia's batik clothing size. Those factors have become the main challenge in creating standardized sizing charts. The economic factor also impacts production. For example, traditional batik garments versus modern industrial batik garments can make the sizing more complex and inconsistent. Furthermore, varied consumer demands in style introduce new complexities in sizing. In the global market, the sizing problem can be narrowed down to the diversity of body shapes, but this factor is enough to raise the sizing complexity perceptions. This makes the task of creating standardized sizing guidelines important [3], [4].

The issue of inconsistent garment sizes extends beyond just women's apparel. Previous research has also revealed concerns regarding the sizing of men's apparel, as indicated by studies that have reported challenges related to inconsistent sizing and limited size availability [5]. Moreover, the dimensions and coding of sizes play a significant role in the level of consumer satisfaction regarding children's apparel. It is worth noting that inconsistencies in sizing across different brands and the presence of perplexing size codes are frequently encountered issues in this domain [6].

Creating standardized sizing guidelines involves consumer profiles and the production team or designer. The understanding and advancements in the fashion industry allow consumers to personalize clothing experiences by self-measure and the seller to customize the product based on the measurements. However, customization can impact the challenges in maintaining standardized sizing while leveraging consumer satisfaction. It also prevents bigger-scale production or manufacturing processes. This will involve stakeholders, fashion designers, and manufacturers in expressing the creative product or market demand [7].

Therefore, the objective of this initial investigation is to ascertain the factors that can facilitate the resolution of the disparate batik size standards in Indonesia so that it can meet the expectations and requirements of individuals who buy and sell batik via online media on e-Marketplaces by utilizing the 3D Scan technology that will be more widely available on mobile phone devices. The study's focus is restricted to examining the perception of prospective users regarding the novelty UKURIN feature. Potential users contribute data by providing information based on video demonstrations showcasing the utilisation of three-dimensional scanning technology, specifically Light Detection and Ranging (LiDAR), integrated inside the most modern versions of mobile phone cameras.

2. Literature Review

This section discusses the state-of-the arts of the related technology in clothing size prediction such as Electronic Marketplace Application, 3D Object Scanning, LiDAR (Light Detection and Ranging), Machine Learning. The framework conducted in this research is also discussed in this section.

2.1. Electronic Marketplace Applications

Increasingly sophisticated technological advancements facilitate economic activities, such as online sales and purchases. The presence of e-marketplaces, whose development increases annually, is one of the factors. E-Marketplace is a platform that facilitates online transactions between vendors and buyers. Consequently, an e-Marketplace is a container or platform that facilitates online purchasing and selling, or as its superset, e-commerce. Through the e-Marketplace, we can locate a variety of products for every need, including bill payment. In addition to fundamental necessities, entertainment and travel tickets, such as movie tickets, train tickets, and even airline tickets, can be purchased on the e-Marketplace. In addition to the ease of transactions, e-marketplaces provide users with numerous discounts and promotions. This is undoubtedly intriguing and presents an opportunity for online store owners to increase sales. Each marketplace has its own characteristics, such as pricing comparison, product variety, logistics services, and reputation, which correspond to the nature of its users. Indirectly, the characteristics of each market reveal the benefits and intended consumers. These advantages and target audiences are utilized by online store owners for business purposes by adjusting which marketplace is best suited for the sale of particular product categories, thereby optimizing sales results.

2.2. 3D Object Scanning Technology

The 3D object scanning technology, also known as 3D scanning or 3D digitization, is a process used to capture the three-dimensional shape and appearance of physical objects in the form of digital data [8]. This technology finds applications in various fields such as manufacturing, design, cultural heritage preservation, healthcare, entertainment, and more. It allows physical objects to be transformed into accurate digital representations that can be manipulated, analyzed, and reproduced.

In delving into the operational intricacies of 3D object scanning technology, a systematic process unfolds [2]. Beginning with Data Capture, where physical object information is collected using a 3D scanner, various techniques decode shape, size, and texture. Methods like Structured Light Scanning, Laser Scanning, Photogrammetry, and Time-of-Flight contribute to a detailed 3D point cloud.

This point cloud, representing the object's position, leads to Point Cloud Generation. Data Processing and Mesh Generation then refine the point cloud, crafting a mesh of interconnected triangles mirroring the object's surface. Texture Mapping adds realism through color data projection.

Post-processing and editing in specialized software fine-tune the 3D model, ensuring precision. The model finds versatile use, from visualization and analysis to animation, 3D printing, and virtual reality. This technology's impact is profound. It drives innovation in manufacturing, aiding quality control and prototyping. Medical realms embrace it, personalizing prosthetics and enhancing surgical planning. Art and cultural heritage benefit from its documentation and restoration abilities.

2.3. LiDAR (Light Detection and Ranging)

LiDAR, an acronym for Light Detection and Ranging, is a remote sensing technique that employs laser pulses to ascertain distances and generate intricate three-dimensional representations of objects and surroundings. It is widely employed across many disciplines like geology, forestry, archaeology, and particularly, in recent times, in the domains of autonomous vehicles and digital mapping applications. The LiDAR technology operates by producing high-frequency laser pulses and subsequently calculating the duration it takes for the light to propagate to a target and return. Through the process of time delay calculation, the LiDAR system is able to accurately ascertain the distance to the object. LiDAR, in conjunction with precise GPS and inertial measurement unit (IMU) data, has the capability to generate very precise and intricate point clouds, which effectively depict the surfaces of various objects or terrains [9].

Regarding the quantification of bodily dimensions through the utilization of mobile devices, notable advancements have been made in the realm of LiDAR technology, particularly in the domain of Apparel Sizing. The utilization of LiDAR technology for body measurements has the potential to aid in the accurate determination of appropriate apparel sizes while online shopping. Individuals have the ability to utilize their cellphones to scan their bodies, thereby obtaining precise size suggestions for various brands and types of apparel.

2.4. Machine Learning

With the advancement of AI technology and increasing number of data collected on the internet, machine learning has gained remarkable attention in the recent decades. Machine learning, a subset of AI, encompass algorithms and techniques that enable computer to learn from data and improve its performance over time without being explicitly programmed. With this ability, machine learning becomes a significant instrument to solve complex prediction problem by processing vast amount of dataset, uncovering hidden patterns, and generating accurate prediction.

In recent years, machine learning along with predictive analytics has shown remarkable performance in various domains such as health, finance, and retail business operations. Within healthcare domain, machine learning has been used to predict disease diagnoses and patient treatment result based on clinical data sources [10]. By determining the pattern in patients' histories, diagnostic imagery, and genomic data, machine learning can generate a mode that offer an early detection of certain disease and help in personalize treatment recommendation. In the financial domain, machine learning has been utilized to advance the risk assessment and market forecasting. Machine learning algorithm can provide comprehensive analysis on the historical financial data to identify market trends [11], predict stock price fluctuation [12], and optimize investments strategy [13]. Meanwhile in retail business operations, the use of machine learning has been flourished platform e-commerce platform. Machine learning algorithm can be used to predict user preferences, suggest products, and tailored product based on individual taste [14]. With this ability, customer can have better engagement and satisfaction. As a result, it can drive user retention and revenue generation.

In the online retail industry, application of machine learning mostly on the area of product recommendation. However, there are still some challenges that could be tackled by machine learning, one of them being predicting clothing size. Usually, when customers buy online clothes, they rely on the traditional size chart that measure height, weight, and waist circumference. Unfortunately, this measurement often fails to capture the diverse human body shape and proportion. This challenge can be addressed with Deep Learning, a subset of machine learning algorithm. The study conducted by Sheikh et al. shows that deep learning is able to process images and extract features that are essential for accurate size estimation [15]. By incorporating multiple user body size and shape, deep learning identifies patterns and preferences, enabling the prediction of sizes for new customers based on the preferences of others with similar body profiles. With the combination of 3D Scanning, LiDAR, we can generate detailed and accurate representations of body shapes, has enriched the quality of input data. The dataset enables the development of comprehensive body profiles, enabling machine learning algorithms to account for intricate body attributes that were previously overlooked.

2.5. Theoretical Framework for Novelty Technology Adoption

The theoretical underpinning of novelty technology adoption is established upon a number of critical aspects that have been found in existing scholarly research. The factors encompassed in this study comprise perceived usefulness, perceived ease of use, social impact, convenience, hedonic incentives, technological facility, and cognitive instrumental processes. In their study, Vahidin et al. in [16] introduced an innovative statistical methodology aimed at analyzing the extent of technological adoption. The framework under consideration takes into account the variables of novelty and complexity within the process of adoption. In their work, Namabira in [17] introduced the framework for novelty technology adoption (Ne-TPAF), which encompasses several elements at the organizational, individual, and social levels that exert influence on the adoption of novelty technology.

In brief, the theoretical framework pertaining to the adoption of novelty technology comprises a range of aspects, such as perceived usefulness, perceived ease of use, organizational factors, individual factors, and social factors. The paradigm above offers a complete understanding of emerging technology adoption.

This study employs the fundamental structure of the Technology Acceptance Model, incorporating three additional variables derived from data collected on a restricted scale. The primary determinant of the adoption of the predictive feature of dress size by online shoppers is found to be Social Influence, which in turn influences Perceived Usefulness. The variables of Computer Self Efficacy and Technological Facility are believed to have an impact on the perception of ease of use. The Extended Technology Acceptance Model framework is shown in Figure 2, but as the product is still novel, the Usage Behavior variable is not employed.

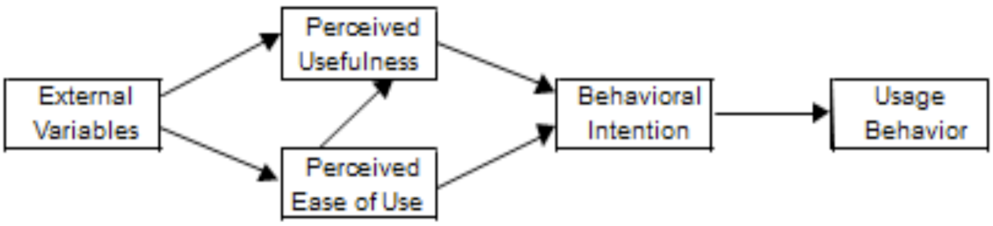

Figure. 2. Extended Technology Acceptance Model

The utilization of the Extended Technology Acceptance Model (TAM) provides researchers with the prospect to examine external factors that could potentially affect the perceptions of usefulness and ease of use, which afterwards have an indirect influence on the intention to engage in the behavior of using the technology. The figure depicting the framework of the Extended TAM as research model utilized is presented in Figure 3 below.

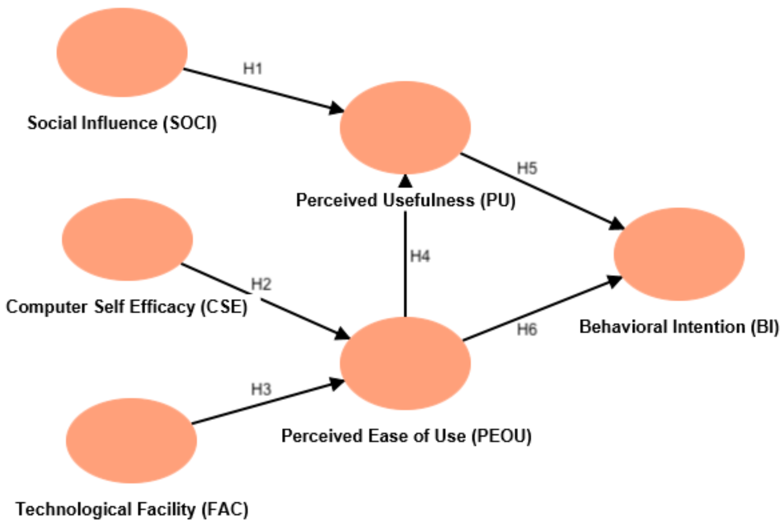

Figure. 3. Research Model

2.6. Research Framework, Model, and Hypotheses

2.6.1. Social Influence (SOCI)

Social influences, as defined by Schmitz et al. in [19] pertain to the extent to which an individual's perception is shaped by the beliefs of significant others regarding the necessity of utilizing a specific technology. The utilization of

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this technology is indicated by the observations made in the immediate surroundings, the studies demonstrated the significant impact of social influence on consumer intention [20], [21]. Similarly, the study conducted by Schomakers in [22] also observed the impact of mobile applications. The significance of the environment that encompasses every customer, whether in the virtual or physical realm, becomes apparent through the behaviors they exhibit. Therefore, it is vital to comprehend the manner in which it accomplishes this objective in order to optimize the implementation of strategies [23].

2.6.2. Computer Self Efficacy (CSE)

Self-efficacy refers to the views held by individuals regarding their capacity to effectively accomplish goals and navigate the various circumstances that impact their life [24]. It is considered a significant factor that directly influences behavior [24]–[26]. Therefore, computer self-efficacy pertains to the perceptions individuals hold regarding their competence in effectively utilizing computers to accomplish tasks and navigate various scenarios [27], [28].

2.6.3. Technological Facility (FAC)

Venkatesh et al. in [20] conducted a study that examined the role of facilitating conditions in a technological setting, specifically in relation to the use of cellular phones [29]. The findings of this study revealed that facilitating conditions are aimed at eliminating obstacles that hinder the utilization of technology, thereby enhancing consumers' ability to effectively engage with the various functions and features of cellular phones, ultimately leading to increased purchase behavior through this medium [30]. In the context of this study, the term technological facility is used to denote facilitating conditions.

2.6.4. Perceived Usefulness (PU)

The concept of Perceived Usefulness pertains to the extent to which an individual has the belief that the utilization of a specific technology will enhance their productivity, efficacy, and overall job accomplishment. In essence, it addresses the inquiry pertaining to the degree of perceived benefits that this technology is anticipated to offer to the individual.

2.6.5. Perceived Ease of Use (PEOU)

The concept of Perceived Ease of Use pertains to an individual's perception regarding the level of ease, simplicity, and minimal effort required when utilizing a particular technology. The inquiry pertains to the level of ease or difficulty associated with the utilization of this particular technology.

2.6.6. Behavioral Intention (BI)

Regarding the concept of Business Intelligence (BI), it can be inferred that it refers to the user's volition to engage in a particular action, as proposed by Davis in [31]. Based on prior research by Venkatesh et al. in [32], it has been established that this particular construct has a direct impact on behavior connected to the use of information and communication technology (ICT). Hence, it can be deduced that the desire to use a product or service has an impact on the genuine attitude of consumers [33]. Based on the provided information, it is possible to formulate the following hypothesis in Table 1 below:

Table. 1. Summary of Research Hypotheses.

Research Hypotheses	**Source**
H1: Social Influence (SOCI) has significant positive direct effect on Perceived Usefulness (PU)	Schmitz et al. in [19]
H2: Computer Self Efficacy (CSE) has significant positive direct effect on Perceived Ease of Use (PEOU)	Compeau & Higgins in [27]; Marakas et al. in [28]

H3: Technological Facility (FAC) has significant positive direct effect on Perceived Ease of Use (PEOU)	Venkatesh et al. in [20]; Migliore et al. in [29].
H4: Perceived Ease of Use (PEOU) has significant positive direct effect on Perceived Usefulness (PU)	Davis in [31]; Venkatesh et al. in [20]
H5: Perceived Usefulness (PU) has significant positive direct effect on Behavioral Intention (BI)	Davis in [31]; Venkatesh et al. in [20]
H6: Perceived Ease of Use (PEOU) has significant positive direct effect on Behavioral Intention (BI)	Davis in [31]; Venkatesh et al. in [20]

3. Research Methodology

This study aims to investigate the determinants of novelty feature adoption in order to predict the size of batik purchased online via e-Marketplaces in the context of Indonesia, a country with a high rate of online purchasing. Data was collected using a questionnaire designed by Nath et al. in [34] based on a measurement instrument previously developed by [31] as a Technology Acceptance Model (TAM) by considering several factors that trigger Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) such as Social Influence (SOCI), Computer Self Efficacy (CSE), and the Technological Facility (FAC). These measuring instruments have been examined to guarantee their accuracy and validity. Figure 4 illustrates the many stages of the research technique, serving as a visual aid to enhance the comprehension of the procedural actions undertaken in this study.

Figure. 4. The Flow of Research Method Steps

This study's population consists of individuals who have purchased clothing from one of the most prominent e-marketplaces in Indonesia. The sampling technique used was purposive (judgmental) sampling with the criterion of having shopped for clothing online, with the goal of the sample having experienced the process of finding the right size for their body size based on non-standard information available on the e-Marketplace from various online shops.

In order for the sample to comprehend the context of the questions posed, data collection begins with operationalizing the indicators used to measure the variables in the theoretical model. Following the completion of the data collection phase, a total of 179 samples were obtained, 17 of which had never browsed for clothing online and therefore could not be used as samples. A total of 162 (or 91%) of the total respondents provided valid data for analysis.

The employed data analysis approach is Partial Least Squares (PLS), a multivariate statistical method capable of accommodating several response and explanatory factors. The present analysis serves as a viable alternative to the approaches of multiple regression and principal component regression analysis, as the former methods exhibit greater robustness. The selection of PLS was motivated by its ability to effectively handle a large number of independent variables, especially in the presence of multicollinearity among these variables. In addition, the Partial Least Squares (PLS) analytic method enables the incorporation of non-normally distributed data and does not necessitate a substantial sample size.

The PLS analysis comprises two distinct components, specifically the *outer model* and the *inner model*. The purpose of the outer model (also known as measurement model) is to assess the validity and reliability of the measurement of the constructs. Meanwhile, the inner model, also referred to as a structural model, illustrates the interconnectedness and interdependencies among variables.

The initial phase of data preparation involves the examination of missing values, outlier testing, and normality tests in order to facilitate subsequent analysis. The analysis of respondent profile demographics encompassed various parameters, including age range, gender, occupational category, average annual frequency of online clothes shopping through e-Marketplaces, preferred e-Marketplaces for clothes shopping, and the range of years of cell phone production utilised. By utilising this demographic, a range of analyses may be conducted to substantiate the findings of the usability test pertaining to the unique feature of clothing size prediction feature namely UKURIN.

As previously defined, the primary objective of this study is to examine the factors that influence individuals' inclination to utilise clothing size prediction functionality through the utilisation of characteristics available on a cellular phone camera. The data in this study was obtained through the utilisation of a questionnaire created by Nath et al. [35], who are the authors responsible for the development of the Technology Acceptance Model [31]. The questionnaire incorporated various variables that are pertinent to mobile-based applications, including Social Influence, Computer Self Efficacy, which has been found to have a strong correlation with Perceived Ease of Use based on the research conducted by Jou et al. in [36], as well as Technological Facility, which refers to the infrastructure support within a system. The selection of this validated measuring equipment was made in order to enhance the validity and reliability of the study. In order to enhance the comprehension of the respondents, the question items were translated into Indonesian and underwent prior assessment of face and content validity from a subset comprising 10% of the sample. Each item was measured using a 5-point Likert scale, a widely employed instrument for assessing perceptions in research studies.

The acquired data will undergo re-testing to assess its validity through the application of convergent validity tests and discriminant validity tests. Convergent validity refers to the extent to which a set of indicators accurately represents both a latent variable and the underlying construct it is intended to measure. The concept of representation can be shown by employing the principle of unidimensionality, which can be quantified by calculating the average value of the extracted variance, commonly referred to as Average Variance Extracted (AVE). The minimum value of the AVE is 0.5. The aforementioned result demonstrates satisfactory convergent validity, indicating that a single latent variable can account for over 50% of the variance observed in its indicators, on average.

Discriminant validity, in the context of research methodology, pertains to the requirement that two distinct conceptual constructs must exhibit sufficient dissimilarity. The underlying premise is that when many indications are joined, they are anticipated to possess multidimensional characteristics. The assessment of discriminant validity employs the criteria established by Fornell-Larcker and Crossloadings. The Fornell-Larcker hypothesis posits that a latent variable exhibits a higher degree of shared variance with its corresponding indicator variable compared to other latent variables. In a statistical interpretation, it is necessary for the average variance extracted (AVE) value of each latent variable to exceed the maximum coefficient of determination (r^2) value obtained with the other latent variable values.

The second requirement pertaining to discriminant validity necessitates that the loading associated with each indication is anticipated to exceed its corresponding cross-loading. If the Fornell-Larcker criteria are utilised to evaluate the discriminant validity of constructs at the latent variable level, it is conceivable for cross-loading to occur at the indicator level. Multicollinearity check will be done by checking the Variance Inflation Factor (VIF) values, number below 5 indicates no multicollinearity.

The F-Square statistic serves as a metric for quantifying the effect size within the context of Partial Least Squares Structural Equation Modelling (PLS-SEM). The concept of R-Square difference refers to the alteration in the R-Square value that occurs when an exogenous variable is eliminated from the model. As stated by Cohen in [37], a value of F-Square more than or equal to 0.02 is classified as small, a value greater than or equal to 0.15 is classified as medium, and a value greater than or equal to 0.35 is classified as large. The coefficient of determination, commonly referred to as R-Square, quantifies the fraction of variability in the response variable that can be explained by the independent variable(s) in a regression analysis. In partial least squares (PLS) analysis, the R-Square statistic is employed as a measure to evaluate the model's ability to explain the observed data. A greater R-Square value indicates a stronger fit between the model and the data. The Standardized Root Mean Square Residual (SRMR) is a metric used to assess the overall fit of a model by quantifying the average magnitude of the differences between observed and expected correlations. It serves as an absolute measure of model fit. A number below 0.10 is deemed to indicate a strong level of fit [38].

4. Results and Discussion

The data acquired during the primary data collecting method is stored in a file format known as CSV (Comma Separated Values). Subsequently, the data undergoes a process of transformation and cleaning to ensure its suitability for analysis. Table 2 presents the findings derived from the examination of the demographic data provided by the respondents.

Table. 2. Demographics of the samples.

	Option	Our Sample (frequency)	Our Sample (%)
Age	Less than 15 years old	0	0
	15 – 20 years old	69	38.6
	21 – 25 years old	24	13.4
	26 – 30 years old	16	8.9
	31 – 35 years old	22	12.3
	Over 35 years old	48	26.8
Gender	Male	93	52
	Female	86	48
Occupation	Students	87	48.6
	Private Company Workers	54	30.2
	Government Officials	5	2.8
	Entrepreneurs	16	8.9
	Others	17	9.5
Shopping Frequency in a Year	Never	17	9.5
	1 – 2	54	30.2
	3 – 5	46	25.7
	6 – 8	17	9.5
	More than 8	45	25.1
Cell Phone Manufacturing Year	After 2021	85	47.5
	2018 – 2021	86	48
	Before 2018	8	4.5

The demographic characteristics of the participants in Table 2 indicate a diverse distribution of data, which enhances the validity of the research findings. Subsequently, participants who had not engaged in online clothing shopping at the e-Marketplace were eliminated from the data analysis due to their failure to fulfil the specified criteria. The survey findings revealed a distinct disparity between students and workers based on their respective occupations. It was observed that a majority of the respondents utilized cell phones manufactured after 2018, which were generally equipped with superior photographic capabilities compared to earlier generations.

To commence the examination of the model's reliability and validity, it is deemed appropriate to consider a minimal factor loading of 0.7 on the latent variables themselves as a reliable benchmark [38]. Table 3 below listed all indicators have factor loading of larger than 0.7.

Table. 3. Factor Loadings of each indicator.

	BI	CSE	FAC	PEOU	PU	SOCI
BI1	**0.944**	0.442	0.594	0.523	0.638	0.640
BI2	**0.928**	0.384	0.542	0.594	0.653	0.714
BI3	**0.954**	0.445	0.624	0.536	0.655	0.665
CSE1	0.378	**0.854**	0.448	0.315	0.298	0.358
CSE2	0.352	**0.826**	0.388	0.331	0.303	0.296
CSE3	0.400	**0.849**	0.344	0.266	0.257	0.367
CSE4	0.369	**0.792**	0.429	0.257	0.218	0.291
FAC1	0.581	0.491	**0.788**	0.540	0.467	0.500
FAC2	0.472	0.420	**0.806**	0.443	0.342	0.446
FAC3	0.483	0.364	**0.811**	0.463	0.517	0.423
FAC4	0.443	0.266	**0.800**	0.470	0.411	0.375
PEOU1	0.587	0.399	0.576	**0.856**	0.596	0.492
PEOU2	0.495	0.282	0.477	**0.905**	0.603	0.533
PEOU3	0.466	0.257	0.493	**0.841**	0.572	0.575
PEOU4	0.507	0.305	0.566	**0.921**	0.628	0.552
PU1	0.622	0.371	0.515	0.600	**0.854**	0.584
PU2	0.579	0.264	0.490	0.607	**0.871**	0.530
PU3	0.549	0.209	0.402	0.537	**0.779**	0.508
PU4	0.600	0.267	0.451	0.582	**0.909**	0.571
SOCI1	0.423	0.299	0.318	0.341	0.366	**0.706**
SOCI2	0.433	0.356	0.320	0.419	0.425	**0.715**
SOCI3	0.663	0.246	0.515	0.587	0.585	**0.857**
SOCI4	0.676	0.366	0.523	0.531	0.602	**0.868**

Following that, we utilise composite reliability indicators and Cronbach's alpha to evaluate the reliability of the constructions. As previously stated, the variables proposed in this study surpass the threshold of 0.7, as proposed by Sekaran in [39]. Similarly, the examination of the average variance extracted (AVE) can be employed to ensure the presence of convergent validity. In accordance with the findings of Geven et al. [40], it is imperative that all indicators are above threshold of 0.5, as depicted in Table 4.

Table. 4. Composite Reliability and Convergent Validity.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.937	0.937	0.959	0.888
CSE	0.851	0.859	0.899	0.690
FAC	0.815	0.817	0.878	0.642
PEOU	0.904	0.906	0.933	0.777
PU	0.876	0.878	0.915	0.730
SOCI	0.802	0.835	0.868	0.624

Next, we will proceed with the examination of discriminant validity. To assess this, we will employ the Fornell & Larcker test and the Heterotrait-Monotrait ratio (HTMT). The study conducted by Fornell and Larcker in [41] test involves the comparison of the square root of the Average Variance Extracted (AVE) for each latent variable with the correlations between that variable and the other variables in the model. The rationale underlying this approach is predicated on the notion that a construct exhibits a higher degree of shared variance with its indicators as opposed to other constructs [42]. Table 5 displayed a comparatively bigger value for the square root of the average.

Following this, the Heterotrait-Monotrait ratio (HTMT) was utlized as a measure of the true correlation between two constructs assuming perfect reliability [38], [42]. The HTMT values obtained were below 0.9, as shown in Table 5. All acquired values exhibit a magnitude less than 0.9. A HTMT value below 0.9 is commonly regarded as a favourable indication, suggesting that the constructs inside the measurement model exhibit adequate differentiation in

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relation to the measured variables or items. This supports the notion that these constructs represent distinct underlying concepts. To further support the discriminant validity, Table 3 was depicting no cross-loading shown.

Table. 5. Discriminant Validity

Fornell-Larcker criterion

	BI	CSE	FAC	PEOU	PU	SOCI
BI	**0.942**					
CSE	0.449	**0.831**				
FAC	0.622	0.485	**0.801**			
PEOU	0.586	0.356	0.602	**0.881**		
PU	0.689	0.328	0.545	0.681	**0.855**	
SOCI	0.715	0.394	0.548	0.609	0.643	**0.790**

Heterotrait-monotrait ratio (HTMT)

	BI	CSE	FAC	PEOU	PU	SOCI
BI						
CSE	0.505					
FAC	0.707	0.576				
PEOU	0.633	0.398	0.694			
PU	0.760	0.372	0.640	0.765		
SOCI	0.798	0.483	0.650	0.698	0.744	

The structure of the model under analysis, along with its corresponding loads, is depicted in Figure 5 below. The path coefficient depicted in Figure 5 below illustrates the direction and magnitude of the relationships. All relationships demonstrate a positive and statistically significant impact, with the exception of Computer Self Efficacy (CSE), which exhibits a weak and non-significant influence on both Perceived Ease of Use (PEOU) and indirectly on Behavioural Intention (BI). The comprehensive path coefficients and corresponding p-values can be seen in Table 7.

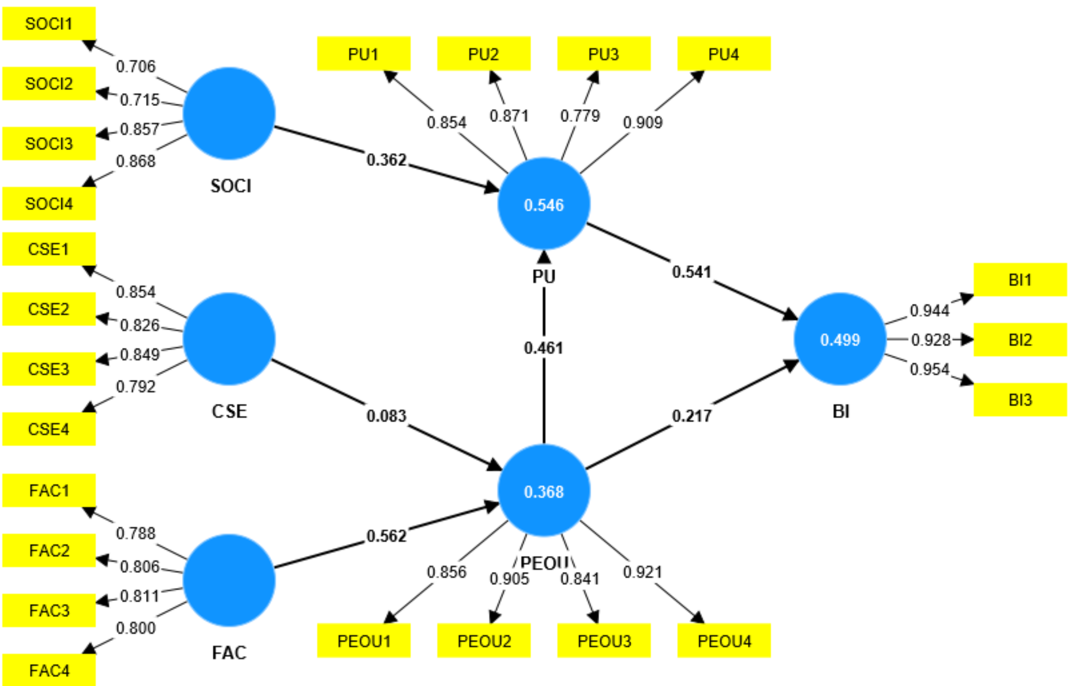

Figure. 5. Outer Model

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4.1. Examination of Hypotheses and Predictive Power

Similarly, Table 6 provides the R^2 values for the second-order constructs, namely Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioural Intention (BI). Table 7 presents an examination of the structural model (R^2) through the analysis of the path coefficients and the explained variance of the endogenous variables. The coefficients given in this analysis serve as indicators of the magnitude of the relationship involving both independent and dependent variables. To ensure the robustness of these path coefficients, a bootstrapping technique was employed, generating 5,000 samples to assess their reliability. Table 8 depicts the total effects of variables toward the Behavioral Intention which indicates that both Social Influence and Technological Facility are significantly affecting Behavioral Intention. The Total Effect refers to the overall impact of an exogenous variable on an endogenous variable, considering both its direct and indirect effects through mediating variables.

Table. 6. The value of R^2.

Variable	**Value of R^2**
Perceived Usefulness (PU)	0.546
Perceived Ease of Use (PEOU)	0.368
Behavioral Intention (BI)	0.499

Table. 7. Path Coefficients and their significance.

Hypotheses	**Path**	**Path Coefficient**	**P values**	**Supported or Not**
H1	SOCI → PU	0.362	0.000	Supported
H2	CSE → PEOU	0.083	**0.190**	Not Supported
H3	FAC → PEOU	0.562	0.000	Supported
H4	PEOU → PU	0.461	0.000	Supported
H5	PU → BI	0.541	0.000	Supported
H6	PEOU → BI	0.217	0.035	Supported

Table. 8. Total Effects and their significance.

Path	**Total Effects**	**P values**
CSE → BI	0.039	**0.210**
CSE → PEOU	0.083	**0.190**
CSE → PU	0.038	**0.218**
FAC → BI	0.262	0.000

FAC → PEOU	0.562	0.000
FAC → PU	0.259	0.000
PEOU → BI	0.466	0.000
PEOU → PU	0.461	0.000
PU → BI	0.541	0.000
SOCI → BI	0.196	0.003
SOCI → PU	0.362	0.000

4.2. Theoretical and Practical Implications

From a theoretical perspective, our analysis incorporates three variables in order to expand upon the conventional Technology Acceptance Model (TAM). These variables are Social Influence (SOCI), Computer Self Efficacy (CSE), and Technological Facility (FAC). All three extended constructions encapsulate the perspective of prospective consumers who seek to make purchases of apparel through an e-Marketplace. A substantial proportion of prospective users have expressed their views on the necessity of a feature that facilitates the prediction of clothing sizes. These opinions emphasise the significance of incorporating such a function into e-Marketplace. Moreover, a significant number of prospective users of UKURIN expressed the necessity for a technologically advanced camera to be integrated into their mobile devices in order to facilitate the accurate measurement of their body dimensions. This fact holds significance from a theoretical perspective as it introduces a novel research perspective that has the potential to yield more comprehensive solutions and expand the scope of technological adoption models.

From the perspective of an e-Marketplace, it is crucial to not only uphold the company's performance but also enhance the satisfaction of both online sellers and shoppers, particularly when it comes to purchasing clothing items with non-standard sizes, such as batik. Consequently, it is of utmost significance for e-Marketplaces to identify the factors that impact the acceptance and utilisation of the dress size prediction feature. Based on the findings of the investigation, it is evident that there is no statistically significant impact of Computer Self Efficacy on Behavioural Intention as shown in Table 7. Consequently, e-Marketplace provider organisations may allocate more resources towards strategies pertaining to Social Influence and Technological Facility. Talsma in [43] conducted a study that posited an indirect hypothesis suggesting that individuals' behaviour in the context of the COVID-19 pandemic renders computer self-efficacy inconsequential. Additional research focused on investigating the correlation between individuals' behaviour in time of COVID-19 pandemic situation and their level of self-efficacy in using computer technology would be necessary in order to establish more conclusive findings.

From an economic perspective, in the context of the post-COVID-19 pandemic, the study conducted highlights the importance of enhancing the performance of Batik Entrepreneurs in order to contribute to the total wealth of the country. It is crucial to acknowledge that any successful endeavours aimed at enhancing economic performance will be indispensable.

5. Conclusion

The findings from the initial research on the elements that impact the adoption of UKURIN, a novel feature that predicts clothing size using users' body dimensions, indicate that Perceived Usefulness is the most influential factor

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in determining users' intention to use UKURIN. The aforementioned discovery aligns with the expanded framework of the Technology Acceptance Model (TAM), wherein Social Influence (SOCI), Computer Self Efficacy (CSE), and Technological Facility (FAC) are incorporated as supplementary variables. This study expands upon prior research conducted on the acceptability of technology, specifically focusing on the influential research conducted by Davis in [31] with the concepts of Perceived Usefulness and Perceived Ease of Use. The text also integrates findings from previous research on the adoption of mobile commerce [31], cloud computing [44], [45], and low impact development [46]. These studies have made significant contributions to the comprehension of the elements that influence the adoption of technology in many circumstances.

The present study utilises an expanded TAM to offer a comprehensive viewpoint on the determinants that impact the adoption of UKURIN. This study examines the impact of social variables, individual self-efficacy, and technological usability on the phenomenon under investigation. The results indicate that individuals see UKURIN as a valuable tool for forecasting clothing size, leading to a favourable impact on their intention to embrace and utilise this feature. The findings of this study carry significant significance for the garment industry, particularly within the framework of the post-COVID-19 pandemic.

The integration of UKURIN into the operations of Batik Entrepreneurs has the potential to significantly augment the economic prosperity of the nation. By effectively utilising users' body proportions to provide precise predictions of garment sizes, UKURIN has the potential to enhance consumer happiness, minimise the occurrence of returns and exchanges, and ultimately improve the overall shopping experience. It is imperative to acknowledge that this initial study offers significant insights into the determinants that impact the adoption of UKURIN. However, additional research is required to authenticate and enhance the validity of these findings.

Subsequent research endeavours may delve into supplementary factors, like the perception of simplicity of use, trustworthiness, and compatibility, in order to get a more all-encompassing comprehension of the process of adoption. The present analysis identified sources that did not provide direct evidence either supporting or refuting the assertion that individuals' behaviour during the COVID-19 pandemic renders computer self-efficacy inconsequential. Nevertheless, this study’s empirical observations substantiate the fact that during the pandemic, individuals are increasingly relying on technology to facilitate communication, engage in online transactions, and streamline various tasks. Consequently, there has been a significant and rapid development in computer self-efficacy, leading to its widespread adoption as a natural attribute possessed by individuals across many demographics. Additional research focused on investigating the correlation between individuals' behaviour amidst the COVID-19 situation and their level of computer self-efficacy would be necessary in order to establish more conclusive findings.

In summary, the initial investigation underscores the significance of Perceived Usefulness in shaping the Behavioural Intention to utilise UKURIN. The adoption of UKURIN can be better understood by the application of the extended Technology Acceptance Model (TAM) paradigm, which incorporates factors such as Social Influence (SOCI), Computer Self Efficacy (CSE), and Technological Facility (FAC). The results of this study have significant ramifications for the textile sector, highlighting the importance of improving the performance of Batik Entrepreneurs during the post-COVID-19 pandemic period.

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