Enhancing Online Batik Shopping Experience through Live Streaming Commerce and the LYFY Application

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Abstract

Online batik shopping often results in buyer dissatisfaction due to discrepancies between product descriptions and the actual items received. Static images and text on e-marketplace platforms are insufficient to convey the intricate details of batik designs, leading to mismatches in customer expectations. To mitigate this issue, Live Streaming Commerce (LSC) features, such as those on Shopee Live, allow sellers to showcase products in real-time, providing more accurate representations. However, sellers face challenges in managing overwhelming volume of comments during live streams, making it difficult to prioritize important queries. LYFY, a comment management app developed to streamline these interactions, aims to address this problem by improving the quality of interaction between live streamers and prospective buyers through filtering important comments. This study examines the determinants affecting the adoption of LYFY by online batik vendors. The research integrates the Task-Technology Fit (TTF), Technology Acceptance Model (TAM), and Expectation-Confirmation Model (ECM) frameworks to evaluate LYFY's performance in fulfilling user requirements. Data were collected from 243 respondents with LSC experience, and the research model underwent evaluation through Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model exhibited high reliability and validity, with values surpassing the suggested thresholds, thereby providing solid support for subsequent analysis. Key factors such as TTF, confirmation, perceived usefulness, ease of use, and satisfaction were examined to determine their impact on user adoption. The analysis revealed that TTF has the strongest influence on confirmation, perceived usefulness, satisfaction, and individual performance. Additionally, perceived ease of use and confirmation substantially influence continuance intentions and satisfaction. These results suggest that enhancing LYFY's task-technology fit and simplifying its user interface are crucial for improving user satisfaction and adoption. By addressing these areas, LYFY can better support live stream sellers, reduce product expectation discrepancies, and improve overall customer experience, particularly in the online batik market.

Keywords: Task Technology Fit (TTF), Technology Acceptance Model (TAM), Expectation-Confirmation Model (ECM), LYFY Application, Live Streaming Commerce

1. Introduction

Sizing issues in online batik shopping, such as inconsistent measurements and poor fit, are a common challenge for both buyers and sellers, often leading to increased returns and customer dissatisfaction. These problems are exacerbated by the lack of standardization in sizing across different brands and designs [1]. Solutions like size prediction tools and detailed size guides help mitigate these issues, but Live Streaming Commerce (LSC) offers an even more dynamic solution. With LSC, buyers can interact directly with sellers in real-time, asking questions about sizing and fit before making a purchase. This interactive feature allows sellers to showcase the product more effectively, providing a clearer understanding of size and style, which reduces the likelihood of returns and enhances the customer experience.

LSC combines live streaming and online shopping. LSC has grown rapidly across China, Thailand, and Indonesia, with varying levels of maturity and success in each market since the pandemic. LSC captivates audiences by offering an engaging and interactive experience, encouraging them to stay tuned longer. It streamlines the customer journey, rapidly moving consumers from brand awareness to making a purchase. Techniques like limited-time discounts or exclusive offers create urgency, motivating immediate action. Companies have observed conversion rates nearing 30%,

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which represents a substantial increase, potentially up to tenfold, compared to those experienced in traditional e-commerce [2].

China is the global leader in live streaming commerce, with a market that has seen explosive growth in the last few years. During the COVID-19 pandemic, the live streaming commerce market expanded dramatically, growing by 196% in 2020 and continuing its upward trend, albeit at a slower pace, with 27% growth in 2022 and 29% in 2023. By the end of 2023, China's LSC market was valued at around $695 billion, driven by platforms such as Taobao Live, Douyin (TikTok's Chinese counterpart), and Kuaishou. The success of LSC in China is largely attributed to the integration of influencers and celebrities who drive impulsive purchasing, making live streaming commerce events must-watch entertainment for many consumers. The market is expected to surpass $1 trillion in two years [3].

In Thailand, live streaming commerce has also gained significant traction, particularly through social media platforms like Facebook Live, TikTok, and LINE Shopping. The market here has grown in parallel with the surge in social media use, with live sales experiencing over 60% growth in the last few years. In 2023, it was estimated that 73% of online shoppers in Thailand had participated in live streaming commerce, a significant increase from earlier adoption rates. This trend mirrors the broader Southeast Asian shift toward social commerce, driven by younger consumers and small businesses looking to engage directly with customers in a more interactive way.

Indonesia has also seen a significant rise in live streaming commerce, particularly on platforms like Shopee Live, Tokopedia Play, and TikTok Live. With its large, young, and digitally savvy population, Indonesia's e-commerce market is projected to grow from $81.8 billion in 2024 to $168 billion by 2029 [4]. Since the pandemic, live streaming commerce has played a central role in this growth, particularly in fashion, beauty, and electronics. Platforms like TikTok and Shopee have capitalized on live streaming commerce, allowing brands and small businesses to reach a wider audience. The penetration of live streaming commerce in Indonesia, particularly among small to medium enterprise (SME), has contributed significantly to the market's overall expansion. This growth has been supported by the increase of internet penetration in Indonesia.

Furthermore, in Indonesia, the popularity of LSC has surged, with a significant portion of internet users engaging in this form of shopping. For instance, approximately 29% of internet users frequently watch live streams from influencers, and 80% of these viewers report purchasing products showcased during these streams [5]. This trend is further supported by the high penetration of e-commerce in the country, where transaction volumes reached IDR 266 trillion in 2020, indicating a robust market for live streaming sales [5]. The integration of live streaming into e-commerce strategies has proven to be an effective method for brands to increase visibility and sales, as it allows for the dissemination of product information in an engaging format [6], [7].

The significant challenge face by live streamer is the psychological pressure associated with live streaming. Streamers often face the burden of creating a persona that resonates with viewers while also being authentic. This balancing act can lead to stress and anxiety, particularly when streamers feel the need to meet sales targets or viewer expectations [8], [9]. Besides that, one of the foremost challenges is the sheer volume and variability of comments that streamers receive in real-time. The rapid influx of viewer comments can be overwhelming, making it difficult for streamers to respond effectively to each one. This situation can lead to missed opportunities for engagement, as streamers may inadvertently overlook important questions or feedback from viewers [10]. The inability to address viewer comments promptly can result in a perception of disengagement, which may deter potential customers from making purchases [11].

Additionally, streamers face the challenge of balancing comment interaction with product presentations, which can create a conflict. Managing both tasks simultaneously can hinder their ability to deliver a strong sales pitch or demonstration. This multitasking often reduces the overall quality of the broadcast, negatively impacting viewer engagement and sales performance. Streamers may end up focusing more on comments or product details, disrupting the smooth flow of the livestream [12].

To address these challenges, LYFY, an application developed by a research team, offers a solution by streamlining comment management during live streams. LYFY helps sellers filter and respond to critical customer inquiries, ensuring more efficient communication and improving the overall live-streaming experience. The app is available on

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the iOS App Store, but further study is required to assess its commercial potential due to low adoption by live streamers. This study integrates various concepts that highlight LYFY role in addressing challenges in live-streaming commerce, emphasizing how its features align with users needs and contribute to improving adoption and satisfaction.

2. Literature Review

This research aims to identify factors that influence the successful adoption of LYFY among online batik sellers. The study integrates the Task-Technology Fit (TTF), Technology Acceptance Model (TAM), and Expectation-Confirmation Model (ECM) frameworks to analyze how well LYFY meets sellers' needs, how easily it can be used, and the level of satisfaction sellers experience with the app. The findings from this research will contribute to a deeper understanding of how LYFY can enhance online batik sales by reducing product specification discrepancies and improving the overall consumer experience in e-Marketplaces. This study uses 243 respondents to ensure statistical power for PLS-SEM analysis and focused on experienced LSC users for relevant insights.

2.1. Task-Technology Fit (TTF)

The TTF framework, proposed by Goodhue and Thompson, asserts that technology's effectiveness depends on how well its capabilities align with the tasks it supports [13]. Over time, the model has expanded to include individual-task and individual-technology fit, providing a comprehensive understanding of technology adoption and user satisfaction. Studies have applied TTF in various fields, such as healthcare, education, and business. Another study [14] also highlighted the impact of technology functionality on task performance, particularly in mobile applications. TTF remains a vital tool for understanding technology adoption and user experiences. Its adaptability and integration with other models highlight its ongoing relevance in various domains of research.

2.2. Technology Acceptance Model (TAM)

The TAM, initially published by Davis, is a prominent theoretical framework designed to elucidate and forecast user acceptance of information technology. The model asserts that two fundamental elements are perceived usefulness (PU) and perceived ease of use (PEOU). Both are essential factors influencing an individual's purpose to utilize a technology. Perceived usefulness indicates the level to which a user believes that employing a certain system will improve their job performance, whereas perceived ease of use signifies the degree to which the user considers the system to be user-friendly [15], [16].

TAM has been extensively applied across various domains, including education, healthcare, and e-commerce, demonstrating its versatility in understanding technology adoption behaviors and many studies have expanded the model to incorporate additional variables to enhance its predictive capabilities [17].

2.3. Expectation-Confirmation Model (ECM)

The ECM is a theoretical framework that explains how users' satisfaction and continued usage of a product or service are influenced by the confirmation of their pre-existing expectations. The core components of ECM include expectations, perceived performance, confirmation (or disconfirmation), and satisfaction. When users' expectations are confirmed, they are likely experiencing satisfaction, which subsequently affects their intention of continuing in utilizing the service or product [18].

Moreover, ECM has been integrated with other theories, such as the TAM, to provide a more comprehensive understanding of user behaviour in various contexts [18], [19]. The model's adaptability makes it a valuable tool for researchers and practitioners aiming to improve service quality and customer satisfaction across different sectors.

2.4. LYFY Application

LYFY is a cutting-edge browser extension that helps live broadcasters manage and improve commercial event comment exchanges. LYFY, an Apple App Store Safari extension, uses advanced machine learning to filter comments in real time. This allows live broadcasters to quickly identify and handle the most important audience questions, enhancing engagement and decreasing oversight of vital discussions. LYFY prioritizes critical comments to help broadcasters focus on important questions and feedback without being overwhelmed by communications.

Its ability to compress analogous comments is impressive. When many viewers ask similar questions, LYFY summarizes them. This streamlines communication, allowing broadcasters to quickly address the most prevalent questions without repetition. Thus, LYFY improves live broadcasts by letting streamers focus on product demos and deeper audience engagement while still answering all viewer questions.

This extension is ideal for e-commerce influencers, companies, and live broadcasters with large audiences and comment volumes. LYFY increases viewer experience by quickly answering crucial questions and connecting with audiences to boost engagement and conversion rates. LYFY plans to expand to more platforms and become a key tool in live streaming commerce, boosting live audience comment management speed and effectiveness. LYFY is a cutting-edge browser extension that helps live broadcasters manage and improve commercial event comment exchanges. LYFY, an Apple App Store Safari extension, uses advanced machine learning to filter comments in real time. This allows live broadcasters to quickly identify and handle the most important audience questions, enhancing engagement and decreasing oversight of vital discussions. LYFY prioritizes critical comments to help broadcasters focus on important questions and feedback without being overwhelmed by communications.

LYFY uses Bidirectional Encoder Representations from Transformers (BERT) to categorize chat messages as either pertinent (product-related) or non-pertinent (irrelevant or informal remarks). BERT's contextual comprehension allows it to accurately filter pertinent communications in real-time. The ADA 002 Text Embedding Model facilitates text similarity research by converting text into embeddings and utilizing cosine similarity to identify related viewer questions and similar comments. k-Nearest Neighbors (k-NN) provides individualized product recommendations by grouping comments and aligning them with appropriate items based on viewer preferences.

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2.5. Theoretical Framework, Model, and Hypotheses

The amalgamation of TTF, TAM, and ECM offers a holistic framework for understanding user continuance intention in various information systems contexts. This hybrid model posits that users' continuance intention is influenced by their perceptions of task-technology fit, their acceptance of the technology, and the confirmation of their expectations post-adoption.

In this framework, TTF assesses how well the technology meets the user's tasks. A good fit between the technology and the user's needs enhances perceived usefulness and ease of use, which are core constructs of TAM [20]. When users perceive that the technology effectively supports their tasks, they are more likely to find it user-friendly and beneficial, which results in increased satisfaction.

The ECM component emphasizes the role of expectation confirmation in shaping user satisfaction and continuance intention. According to ECM, if the actual performance of the technology meets or exceeds users' expectations, it results in positive confirmation, which enhances satisfaction and encourages continued use [21], [22]. Conversely, if the technology fails to meet expectations, users may experience dissatisfaction, leading to a decline in usage intentions.

This combined model as illustrated in Figure 1 below has been validated in various studies, demonstrating its applicability across different domains, such as cloud computing and other environments [20], [23], [24]. By combining these three models, researchers can better understand the multifaceted nature of user behavior and the factors that drive continued engagement with technology.

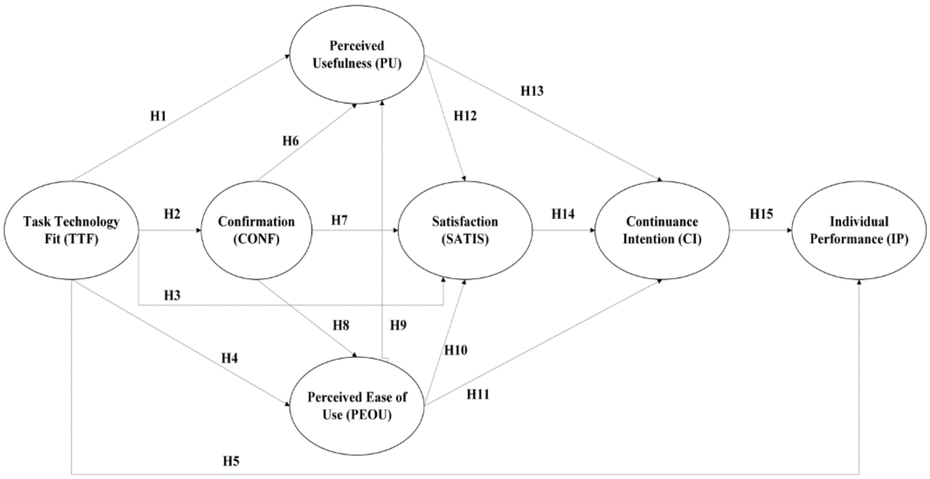

Figure 1. Theoretical Model

2.5.1. Task Technology Fit (TTF)

TTF is a theoretical framework that examines the alignment between the capabilities of technology and the requirements of tasks that users need to perform. The TTF model posits that the effectiveness of technology is contingent upon its ability to support the specific tasks that users engage in, thereby influencing their performance and satisfaction with the technology [25]. In the context of mobile banking, the TTF model has been employed to analyze how well mobile applications support banking tasks, revealing that a good fit enhances user performance and satisfaction. Similarly, in healthcare settings, TTF has been used to evaluate the effectiveness of electronic clinical data systems, highlighting the importance of task-technology alignment for successful implementation [26].

2.5.2. Perceived Usefulness (PU)

PU is a key notion in the TAM, defined as the extent to which an individual believes that utilizing a specific technology improves their job performance [27], [28]. This belief significantly influences an individual's intention to adopt and utilize technology, as users are more likely to embrace systems they perceive as beneficial to their productivity. Research has consistently shown that PU is a strong predictor of technology acceptance, with empirical studies indicating that it accounts for a substantial portion of the variance in user behavior [29].

2.5.3. Perceived Ease of Use (PEOU)

PEOU is a critical construct in the TAM, defined as the degree to which a person believes that using a particular system will be free of effort [15], [29]. This concept posits that when people regard a technology as easy to use, they are more inclined to accept and employ it efficiently. Research indicates that PEOU significantly influences users' behavioral intentions, as it affects their perceived usefulness of the technology [30].

2.5.4. Confirmation (CONF), Satisfaction (SATIS), and Continuance Intention (CI)

The ECM is a theoretical framework that explains user behavior regarding the continued use of information systems and services. It posits that users' satisfaction and their intention to continue using a technology are influenced by the confirmation of their initial expectations after using the system. The model consists of three primary variables: Confirmation, Satisfaction, and Continuance Intention. Confirmation refers to the extent to which users perceive that their initial expectations about a system's performance have been met after actual use. This disconfirmation process is critical as it directly influences user satisfaction [31]. Satisfaction is the emotional response users have towards their experience with the system, which is shaped by the confirmation or disconfirmation of their expectations. High satisfaction levels typically lead to positive attitudes towards the system and enhance the likelihood of continued use [32]. Continuance Intention is the user's intention to continue using the system in the future. It is influenced by both satisfaction and confirmation, where higher satisfaction resulting from positive confirmation results in an enhanced commitment to persist in utilizing the technology [33].

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2.5.5. Individual Performance (IP)

Individual performance is a critical measure of Information Systems (IS) success, as it reflects how effectively users can achieve their tasks and objectives using the system. The DeLone and McLean IS Success Model serves as a foundational framework for assessing IS success, emphasizing the importance of individual performance as a key outcome of system quality, information quality, and user satisfaction [34]. Individual Performance can be defined as the extent to which an individual effectively utilizes an information system to enhance their productivity and achieve personal or organizational goals. Research indicates that high-quality systems lead to improved individual performance by providing accurate, timely, and relevant information, which in turn enhances decision-making and task execution [35].

Based on the above description of the variable, the next argument can be written in Table 1:

Table 1. Summary of Hypotheses formulated in this study.

Hypotheses formulated in this study	Source
H1: Task Technology Fit (TTF) positively influences Perceived Usefulness (PU)	[36]
H2: Task Technology Fit (TTF) positively influences Confirmation (CONF)	[37]
H3: Task Technology Fit (TTF) positively influences Satisfaction (SATIS)	[37]
H4: Task Technology Fit (TTF) positively influences Perceived Ease of Use (PEOU)	[36]
H5: Task Technology Fit (TTF) positively influences Individual Performance (IP)	[26], [38]
H6: Confirmation (CONF) positively influences Satisfaction (SATIS)	[31], [32], [33]
H7: Confirmation (CONF) positively influences Perceived Usefulness (PU)	[31], [32], [33]
H8: Confirmation (CONF) positively influences Perceived Ease of Use (PEOU)	[31], [32], [33]
H9: Perceived Ease of Use (PEOU) positively influences Perceived Usefulness (PU)	[27], [29], [39]
H10: Perceived Ease of Use (PEOU) positively influences Satisfaction (SATIS)	[31], [32], [33]
H11: Perceived Ease of Use (PEOU) positively influences Continuance Intention (CI)	[31], [32], [33]
H12: Perceived Usefulness (PU) positively influences Satisfaction (SATIS)	[31], [32], [33]
H13: Perceived Usefulness (PU) positively influences Continuance Intention (CI)	[31], [32], [33]
H14: Satisfaction (SATIS) positively influences Continuance Intention (CI)	[31], [32], [33]
H15: Continuance Intention (CI) positively influences Individual Performance (IP)	[40]

3. Methodology

Figure 2 delineates the procedural steps of this study. The process commences with the articulation of the problem statement, wherein this study delineates the particular issue or inquiry it seeks to resolve. This phase is essential since it establishes the direction and emphasis of the entire research process.

Figure 2. Flow of Research Method Steps

This study will thereafter evaluate the literature to analyze existing research and information pertinent to the issue. This aids in comprehending prior accomplishments and pinpointing deficiencies or domains requiring additional investigation. Upon examining the literature, the subsequent stage is to identify plausible elements derived from prior studies, which entails articulating potential variables or influences that may impact the issue under investigation.

Subsequently, the study reviews and selects an appropriate framework that guides the structuring of the research and ensures the inclusion of all essential components. Upon establishing the framework, the hypothesis is articulated, delineating the predictions or assumptions that this study will evaluate.

The subsequent steps entail data collection to obtain the requisite information for hypothesis testing, succeeded by data analysis, wherein this study assesses the data to derive conclusions and ascertain if the hypothesis is corroborated or denied. This procedure guarantees a methodical and structured approach to tackling the research issue.

3.1. Population and Sample

The population of this study is made up of LSC participants, including sellers, managers, and customers from popular Indonesian e-marketplaces. Purposive (judgmental) sampling was used, with participants having to have prior experience selling or purchasing via live streaming platforms such as Shopee Live and TikTok Live. This method is advantageous because it allows the study to gather focused insights from individuals who can provide informed perspectives on the adoption of LYFY. However, its limitations include the risk of selection bias, as the sample may not fully represent the broader population. Despite these limitations, purposive sampling aligns with the study's objective of understanding LYFY's potential among experienced users, making it the most appropriate choice for this context. This technique aimed to provide the sample population with direct experience of the live streaming commerce process. To make certain that the participants comprehended the context of the study questions, the data collection technique commenced with the operationalization of the indicators employed to assess the variables in the theoretical model. Subsequent to data collection, 243 valid replies were obtained and processed. This sample size was selected to ensure sufficient statistical power and validity in capturing a diverse range of user feedback, particularly for evaluating the effectiveness, ease of use, and overall user satisfaction with LYFY.

3.2. Analysis Method

Partial Least Squares (PLS), a multivariate statistical approach, was used to analyze the data. PLS is more robust than regression, especially when independent variables are multicollinear. It handles non-normal data and lower sample sizes well. This technique was particularly suited for this study as it allows for simultaneous evaluation of both measurement and structural models, making it ideal for exploratory research involving latent constructs. The outer model (measurement model) assesses construct validity and reliability, while the inner model (structural model) explores variable linkages and dependencies.

3.3. Data Collection

The demographic analysis of the respondents covered variables such as age, gender, education level, occupational category within LSC, and experience with LSC, alongside the frequency of use and the age of the mobile devices used for accessing LSC. These demographic factors were crucial in analyzing the intention to continue using LYFY, a browser extension designed to manage comments in live streaming commerce. Since most of the respondents had never used the LYFY application, a video illustration was created to demonstrate how LYFY could help manage interactions between sellers and buyers. The data was collected using a questionnaire adapted from Cheng (2020) that incorporated variables relevant to browser applications, including TTF, TAM, and ECM. The responses were measured using a 5-point Likert scale.

3.4. Validity, Reliability, and Goodness of Fit

The validity of the collected data was assessed through convergent and discriminant validity tests. Convergent validity was evaluated through the Average Variance Extracted (AVE), where a minimum AVE of 0.5 indicates that a latent variable explains more than 50% of the variance in its indicators. Discriminant validity was tested using the Fornell-Larcker criterion and cross-loadings to ensure conceptual constructs were distinct. Additionally, multicollinearity was assessed with the Variance Inflation Factor (VIF), with values under 5 signifying the absence of multicollinearity. The F-Square statistic was employed to assess effect size in the PLS-SEM model, while The R-Square values evaluated the model's explanatory capacity. The Standardized Root Mean Square Residual (SRMR) was utilized to assess model fit, with values under 0.10 signifying a robust fit.

4. Results and Discussion

The survey was conducted using Google Forms and facilitated through Populix, a data collection service. The data obtained from the primary data collection method was stored in a CSV (Comma Separated Values) file format.

Following this, the dataset was transformed and cleaned to assure its appropriateness for examination. Table 2 displays the outcomes of the demographic data submitted by the respondents.

Table 2. The demographics characteristics of the samples.

	Item	Frequency of Sample	Percentage of Sample (%)
Age Group	20 years old or younger	44	18
	21 – 30 years old	125	51
	31 – 40 years old	46	19
	41 – 50 years old	21	11
	51 years old or older	7	1
Gender	Male	77	32
	Female	166	68
Education	Post Graduate	14	6
	Graduate	103	42
	High School	126	52
LSC Role	Business Owner	58	24
	Business Manager	20	9
	Customer	165	67
LSC Frequency	Random	86	35
	On average once a day	36	15
	On average once a week	73	30
	On average once a month	48	20
LSC Experience	Less than a year	147	60
	1 – 2 years	55	23
	More than 2 years	41	17
Phone Year	After 2022	120	49
	2018 – 2022	113	47
	Before 2018	10	4

This study's respondent profile centers on individuals engaged in LSC across platforms like Shopee Live, TikTok Live, and various other LSC platforms, with roles as business owners, managers, or customers. The sample comprises 243 respondents, with the majority (51%) aged between 21 and 30 years. Females made up 68% of the sample, showing a significant gender skew toward women in live streaming commerce activities. The gender imbalance may influence the generalizability of the results, as male users may have different adoption behaviors and preferences.

In terms of education, 52% of respondents had completed high school, and 42% held graduate degrees. Usage patterns showed that 35% of respondents accessed LSC randomly, while 30% engaged once a week. Most respondents (60%) had less than a year of experience with LSC, emphasizing the platform's recent rise in popularity. Additionally, 49% of respondents used mobile phones produced after 2022, suggesting that modern smartphones play a crucial role in LSC engagement. Overall, the data indicates that LSC users are primarily young, female customers with varying levels of experience, using up-to-date mobile technology to participate in live streaming commerce.

4.1. Validity and Reliability

To begin assessing the model's reliability and validity, a minimal factor loading 0.7 on latent variables is typically considered an appropriate benchmark for reliability [41]. As shown in Table 3, all indicators in this table meet the recommended factor loading threshold of 0.7 or higher, which suggests that the measurement model is reliable. The indicators are strongly correlated with their respective latent variables, providing good support for the validity of the proposed constructs.

Table 3. Factor Loadings of each indicator.

	CI	CONF	IP	PEOU	PU	SATIS	TTF
CI1	0.893	0.695	0.761	0.755	0.723	0.776	0.629
CI2	0.922	0.686	0.715	0.717	0.666	0.737	0.597
CI3	0.912	0.633	0.719	0.656	0.653	0.712	0.577
CI4	0.884	0.664	0.736	0.699	0.650	0.744	0.577
CONF1	0.662	0.899	0.713	0.693	0.770	0.706	0.775
CONF2	0.623	0.896	0.718	0.682	0.724	0.665	0.703
CONF3	0.702	0.883	0.708	0.659	0.742	0.689	0.724
IP1	0.765	0.754	0.899	0.723	0.733	0.709	0.644
IP2	0.735	0.644	0.886	0.708	0.694	0.720	0.606
IP3	0.653	0.721	0.870	0.711	0.715	0.693	0.663
PEOU1	0.527	0.510	0.528	0.770	0.544	0.593	0.466
PEOU2	0.674	0.677	0.706	0.902	0.712	0.720	0.641
PEOU3	0.739	0.695	0.736	0.886	0.682	0.727	0.652
PEOU4	0.712	0.689	0.757	0.851	0.706	0.751	0.661
PU1	0.660	0.740	0.735	0.665	0.890	0.662	0.737
PU2	0.690	0.778	0.753	0.736	0.902	0.696	0.728
PU3	0.670	0.726	0.646	0.666	0.870	0.677	0.688
PU4	0.614	0.704	0.714	0.684	0.870	0.664	0.710
SATIS1	0.695	0.676	0.676	0.692	0.679	0.835	0.617
SATIS2	0.745	0.708	0.730	0.749	0.686	0.899	0.653
SATIS3	0.726	0.663	0.694	0.736	0.671	0.910	0.638
SATIS4	0.726	0.657	0.705	0.709	0.650	0.867	0.635
TTF1	0.589	0.739	0.653	0.661	0.740	0.654	0.890
TTF2	0.597	0.764	0.675	0.650	0.746	0.621	0.904
TTF3	0.596	0.736	0.628	0.626	0.700	0.657	0.893
TTF4	0.539	0.656	0.575	0.583	0.667	0.621	0.834

All latent variables (CI, CONF, IP, PEOU, PU, SATIS, and TTF) shown in Table 4 have composite reliability Values exceeding 0.9 indicate a substantial level of internal consistency for each construct, while their AVE values exceed 0.7, demonstrating excellent convergent validity, meaning that the indicators reliably reflect their respective latent variables and share a strong correlation with them [41].

Table 4. Composite Reliability and Convergent Validity.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CI	0.925	0.925	0.946	0.816
CONF	0.873	0.873	0.922	0.797
IP	0.862	0.864	0.915	0.783
PEOU	0.875	0.886	0.915	0.729
PU	0.906	0.907	0.934	0.780
SATIS	0.901	0.902	0.931	0.771
TTF	0.903	0.906	0.932	0.776

The discriminant validity assessment using the Fornell-Larcker criterion in Table 5 shows that each construct (CI, CONF, IP, PEOU, PU, SATIS, and TTF) has a higher correlation with its own indicators than with other constructs, confirming that discriminant validity is met.

Table 5. Discriminant Validity (Fornell-Larcker criterion).

	CI	CONF	IP	PEOU	PU	SATIS	TTF
CI	0.903						
CONF	0.742	0.893					
IP	0.813	0.798	0.885				
PEOU	0.784	0.760	0.807	0.854			
PU	0.746	0.835	0.807	0.779	0.883		
SATIS	0.823	0.770	0.799	0.822	0.764	0.878	
TTF	0.660	0.823	0.720	0.716	0.810	0.724	0.881

Additionally, the Heterotrait-Monotrait (HTMT) ratio was evaluated to further ensure the distinctiveness of constructs as shown in Table 6. With HTMT values below the recommended threshold of 0.90, the analysis confirms that the constructs are sufficiently distinct from one another. Combining both Fornell-Larcker and HTMT results provides strong evidence that the constructs in the model are valid, reliable, and measure different concepts.

Table 6. Discriminant Validity (Heterotrait-monotrait ratio).

	CI	CONF	IP	PEOU	PU	SATIS	TTF
CI							
CONF	0.825						
IP	0.908	0.921					
PEOU	0.863	0.862	0.920				
PU	0.814	0.939	0.913	0.870			
SATIS	0.901	0.868	0.907	0.921	0.847		
TTF	0.721	0.925	0.815	0.797	0.895	0.804	

4.2. Hypotheses Testing

In hypothesis testing, as shown in Table 7, the relationships between variables are evaluated through multiple steps. First, the R-squared (R^2) values are calculated to assess how much of the variance in each dependent variable is explained by the independent variables. Next, the path coefficients are measured to determine the strength and direction of these relationships. Alongside this, the significance of each path is tested using p-values, where a value below 0.05 typically indicates a statistically significant relationship. Finally, the total effects, including both direct and indirect influences, are measured to provide a comprehensive view of how variables impact each other across the entire model.

Table 7. R-square Values.

	R-square	R-square adjusted
Continuance Intention (CI)	0.727	0.723
Confirmation (CONF)	0.677	0.676
Individual Performance (IP)	0.720	0.718
Perceived Ease of Use (PEOU)	0.603	0.599
Perceived Usefulness (PU)	0.745	0.743
Satisfaction (SATIS)	0.734	0.730

The R-squared values in the table indicate the proportion of variance in each dependent variable that is explained by the model. Satisfaction ($R^2 = 0.751$) has the highest explanatory power, showing that 75.1% of its variance is predicted by the model, indicating a very strong fit. Continuance Intention ($R^2 = 0.670$) and Confirmation ($R^2 = 0.678$) also show strong predictive capabilities, with over 67% of their variance explained. Perceived Usefulness ($R^2 = 0.656$) and Individual Performance ($R^2 = 0.661$) demonstrate similarly strong predictive accuracy, explaining over 65% of their respective variances. The Perceived Ease of Use exhibits a moderate R-squared value of 0.513, indicating that the model explains 51.3% of the model's variance. Overall, the model shows strong explanatory power across most variables, especially for Satisfaction, Continuance Intention, and Confirmation, indicating that the independent variables are effective at predicting users' experiences and behaviors with LYFY.

Table 8 shows the hypothesis testing results, where the path coefficients and p-values determine whether the hypotheses are supported. For most hypotheses, the p-values indicate significant relationships, suggesting that the proposed relationships are well-supported. However, hypotheses H3 and H12 are not supported, as their p-values (0.376 and 0.208, respectively) exceed the standard significance level of 0.05, indicating that these paths do not have statistically significant effects in the model. This suggests that the proposed relationships in H3 and H12 do not hold in this context, while the other hypotheses demonstrate significant and meaningful relationships, validating the model for those specific paths. Overall, the model is largely supported, except for the non-significant results in H3 and H12. The non-significant result of H3 could be explained by the possibility that perceived ease of use and expectation confirmation have a greater impact on LYFY satisfaction than activity-technology alignment. Despite having a major influence on Continuance Intention (CI), users are likely to view the PU of LYFY as less significant than other criteria for H12. These findings highlight the complexity of user satisfaction factors without necessarily pointing to model issues.

Table 8. Path Coefficients and their significance.

Hypotheses	Path	Path Coefficient	Total Effects	P values	Support
H1	TTF → PU	0.303	0.810	0.007	Supported
H2	TTF → CONF	0.823	0.823	0.000	Supported
H3	TTF → SATIS	0.094	0.724	0.376	Not Supported
H4	TTF → PEOU	0.281	0.716	0.001	Supported
H5	TTF → IP	0.325	0.720	0.000	Supported
H6	CONF → SATIS	0.210	0.538	0.019	Supported
H7	CONF → PU	0.375	0.522	0.000	Supported
H8	CONF → PEOU	0.528	0.529	0.000	Supported
H9	PEOU → PU	0.278	0.292	0.000	Supported
H10	PEOU → SATIS	0.498	0.499	0.000	Supported
H11	PEOU → CI	0.240	0.488	0.008	Supported
H12	PU → SATIS	0.125	0.125	0.208	Not Supported
H13	PU → CI	0.194	0.283	0.004	Supported
H14	SATIS → CI	0.478	0.487	0.000	Supported
H15	CI → IP	0.598	0.598	0.000	Supported

The results show that TTF has strong and significant effects on key variables such as CONF, PU, and PEOU, highlighting the importance of aligning technology with user tasks to enhance these outcomes. Additionally, CI significantly influences IP, reinforcing the idea that users who intend to continue using the system tend to perform better. Furthermore, the Perceived Ease of Use has a positive effect on continuance intention, indicating that users are more inclined to persist in using a system when they consider it user-friendly. However, the 2 non-significant relationships indicate the relationships from TTF and PU may not directly affect user's SATIS in this context, implying other factors may play a more critical role in determining satisfaction. Overall, these findings underscore the importance of task-technology alignment and ease of use in improving user performance and experience.

4.3. Study Practical Implications

For the LYFY development team, the key takeaway is to prioritize enhancing the fit between the app's functionalities and the tasks of live stream sellers. This could involve refining existing features such as intelligent comment filtering and improving the user interface to ensure ease of use. The prioritization feature enables streamers to focus on high

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value interactions, such as addressing buyer questions, which can directly enhance the overall user satisfaction. Additionally, since confirmation plays a vital role in user satisfaction and intention to continue using LYFY, providing clear tutorials, onboarding processes, and feature demonstrations will help users quickly understand the value of the app. Furthermore, ensuring that users' expectations are met or exceeded through continuous updates and improvements will reinforce their satisfaction and commitment to using LYFY, ultimately improving their performance during live streams.

4.4. Limitation and Future Research

Although purposive sampling works well for identifying seasoned users, it may restrict the findings' generalizability. Additionally, because individuals may overstate or understate their experiences, self-reported statistics may contain response bias. The conclusions' applicability in other areas with distinct cultural, technological, or economic contexts may be diminished by the emphasis on Indonesia's live streaming commerce market. Although the application of TTF, TAM, and ECM yields insightful information, a more thorough understanding might be obtained by including elements like user motivation, social presence, and trust. To fill in these gaps and advance this research, future studies could examine LYFY's adoption in different areas, employ longer-term studies to monitor changes over time, and explore qualitative studies to provide deeper insights into Satisfaction drivers, revealing nuances not captured by the current model.

5. Conclusion

Despite the promising functionality of LYFY in managing live streaming commerce interactions, its adoption among users remains low. LYFY is designed to streamline comment management for live streamers, enabling better engagement with their audience and improving overall performance. However, challenges in user adoption persist, necessitating further exploration of the factors influencing its uptake. This study used a combination of the TTF, TAM, and ECM frameworks to analyze how well LYFY meets the needs of its users, drawing data from respondents. The results indicated that TTF has a substantial impact on PU, PEOU, and SATIS, which are essential factors for ongoing usage and enhanced IP.

The study highlights that while LYFY's features align well with users' tasks, further development is needed to enhance user onboarding and interface usability. Providing clearer feature demonstrations, promptly collecting and implementing user feedback to address pain points, and ongoing updates to meet user expectations can drive higher satisfaction and adoption. Moving forward, LYFY's development team should focus on refining task-technology alignment and improving the overall user experience to maximize its potential in the live streaming commerce market.

6. Declarations

6.1. Author Contributions

Conceptualization: T.W., W.B.W., Y.E.O., I.M., and Y.S.S.; Methodology: T.W. and W.B.W.; Software: T.W. and W.B.W.; Validation: T.W., I.M., and Y.E.O.; Formal Analysis: T.W., I.M., and Y.E.O.; Investigation: T.W.; Resources: Y.S.S.; Data Curation: T.W. and W.B.W.; Writing Original Draft Preparation: T.W., W.B.W., and Y.E.O.; Writing Review and Editing: T.W., W.B.W., and Y.E.O.; Visualization: Y.S.S. All authors have read and agreed to the published version of the manuscript

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

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

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