THE EFFECTIVENESS OF LIVE-STREAMING COMMERCE IN DRIVING CONSUMER ENGAGEMENT AND PURCHASING INTENTION

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BY

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DECLARATION

I hereby declare that:

(1) This undergraduate FYP is the end result of my own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Sole contribution has been made by me in completing the FYP.

(4) The word count of this research report is 11,000 words.

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CE	Consumer Engagement
eWOM	Electronic Word-of-Mouth
IQ	Information Quality
KPI	Key Performance Indicator
LC	Live Streaming Host Characteristics
PI	Purchasing Intention
SMM	Social Media Marketing
UGC	User-Generated Content

PREFACE

This research project is undertaken as a requirement for the Bachelor of International Business program offered by the Faculty of Accountancy and Management at University Tunku Abdul Rahman Sungai Long. The study was conducted between October 2024 and May 2025.

The primary objective of this research is to evaluate the effectiveness of live-streaming commerce platforms in driving consumer engagement and purchasing intention. Specifically, we examine how factors such as information quality, consumer engagement, live streaming host characteristics and time-scarcity influence consumer's engagement behaviours and their intention to purchase via live-stream sessions.

By analysing the relationships among these factors and consumer responses to live-streaming commerce, this study aims to provide educators, marketers, and platform developers with actionable insights into designing more compelling live-stream experiences. Ultimately, the findings will support the formulation of strategic approaches to enhance consumer engagement and conversion rates in the evolving landscape of digital retail.

ABSTRACT

The rapid proliferation of live-streaming commerce has revolutionized e-commerce by driving consumer engagement and purchasing intention. This study explores the effectiveness of live-streaming platforms in influencing consumer behaviour, with a focus on broadcasters' roles, real-time interaction, and psychological mechanisms that reduce perceived uncertainty. Employing signalling theory and consumer motivation theory, the research examines dual routes through which broadcasters impact consumers: product-centred and social-interaction-centred routes. Findings reveal that broadcasters' physical characteristics and personal values serve as critical signals to build trust and improve product fit perceptions, ultimately enhancing purchase intention. Besides, to support the hypothesis by evidence, this research will conduct a online questionnaire to collect primary data and prepare to analysis. The target will be located to young adults and undergraduate level students and above in University Tunku Abdul Rahman's campus in Malaysia Moreover, the result will be interpreted to justify the research objectives and problems that may provide some acknowledge on live-streaming commerce categories in the future.

Keywords: Consumer Engagement, Live-Streaming Commerce, Purchasing Intention, Social Media Marketing, Time-Scarcity

CHAPTER 1 RESEARCH OVERVIEW

1.0 Research Title

The Effectiveness of Live-Streaming Commerce Platform in Driving Consumer Engagement and Purchasing Intention.

1.1 Research Background

The widespread adoption of live streaming has significantly facilitated its integration with marketing campaigns, driving a surge in the growth of e-commerce economies. Industry reports reveal that the market size of live-streaming commerce in China reached 433.8 billion yuan in 2019 and was projected to surpass 900 billion yuan by 2020 (Del Mastio, N, 2021). Live streaming has proven especially effective for introducing and selling experience-driven products such as clothing and cosmetics. For instance, in 2019, over 10,000 internet celebrities promote various products through Taobao live streaming, such as cosmetic products, clothing, and food (Cai and Whon, 2019).

This phenomenon starkly contrasts with the relatively low purchase rates of experience-driven products on traditional e-commerce platforms, where consumers often perceive high levels of uncertainty (Tamer, 2021). For example, buyers may question whether certain clothing items will suit them or doubt the credibility of sellers. In contrast, live-streaming commerce reduces these uncertainties through real-time demonstrations and interactions (Zhang et al., 2022). A notable example is Jiaqi Li, a well-known broadcaster who sold 15,000 lipsticks within just five minutes during one of his live-streaming sessions (Xuan J, 2021). Most viewers trust his recommendations and make immediate purchase decisions. Hence, understanding how broadcasters minimize perceived uncertainty and significantly enhance the online purchase of clothing and cosmetics presents an intriguing research opportunity (Zhang et al., 2022).

Research on live-streaming commerce is still in its infancy. Existing studies primarily focus on identifying predictors of purchase intentions (PI) from the perspectives of traditional e-commerce platforms and consumers. However, there is a lack of research exploring the usage

of live streaming in influencing purchase intentions of customer in e-commerce (Zhang et al., 2022). To address this gap, this study aims to examine how the live streaming elements such as broadcaster characteristics contribute to reducing consumer uncertainty and boosting purchase intentions.

1.2 Research Problem

The rapid growth of live-streaming commerce platforms has transformed consumer behaviour, creating new dynamics in engagement and purchasing decisions. Despite its popularity, questions remain about how these platforms effectively engage consumers and drive their purchasing intentions. Key challenges include understanding the specific factors that contribute to consumer engagement, such as interactive features, trust in broadcasters, and the role of time-limited promotions. Furthermore, while live-streaming commerce is praised for reducing perceived uncertainties in online shopping, it is unclear how effectively it builds long-term trust and loyalty among consumers (Luo, Lim, Cheah, Lim, & Dwivedi, 2023) .

Another problem lies in identifying the role of different elements in live-streaming commerce, such as product presentation styles, broadcaster characteristics, and the integration of social interaction. How do these elements work together to influence purchasing intentions? Additionally, the effectiveness of these platforms may vary across different consumer demographics and product categories, presenting another layer of complexity (Luo, Lim, Cheah, Lim, & Dwivedi, 2023).

This study aims to explore these challenges by investigating the mechanisms through which live-streaming commerce platforms engage consumers and drive their purchasing intentions. Insights from this research can help businesses optimize their strategies and improve consumer experiences on live-streaming platforms.

1.3 Research Objectives

1. To determine if there is a significant relationship between Consumer Engagement and Purchasing Intention towards the live-streaming commerce.
2. To determine if there is a significant relationship between Live Streaming Host's Characteristics and Purchasing Intention towards the live-streaming commerce.
3. To determine if there is a significant relationship between Information Quality and Purchasing Intention towards the live-streaming commerce.
4. To determine if there is a significant relationship between Time-Scarcity and Purchasing Intention towards the live-streaming commerce.

1.4 Research Questions

1. What is the relationship between Consumer Engagement and Purchasing Intention towards the live-streaming commerce?
2. What is the relationship between Live Streaming Host's Characteristics and Purchasing Intention towards the live-streaming commerce?
3. What is the relationship between Information Quality and Purchasing Intention towards the live-streaming commerce?
4. What is the relationship between Time-Scarcity and Purchasing Intention towards the live-streaming commerce?

1.5 Research Significance

This research provides critical insights into the factors that make live-streaming commerce platforms effective in driving consumer engagement and purchasing intention. Businesses can use these findings to optimize their marketing and operational strategies, such as creating more engaging live-stream content, utilizing data analytics to predict consumer preferences, and designing interactive features to enhance consumer experiences. By understanding what influences consumer behaviour in live-streaming environments, companies can better allocate resources to areas with the highest potential for revenue growth, build stronger brand loyalty, and increase customer retention. Ultimately, this contributes to the sustainable development of

the live-streaming commerce industry and positions businesses competitively in the dynamic e-commerce landscape (Luo, Lim, Cheah, Lim, & Dwivedi, 2023).

Besides, a significant gap in the existing literature on live-streaming commerce by focusing on the intersection of consumer behaviour, technology, and social interaction. It examines underexplored aspects such as the role of broadcasters, the impact of real-time communication, and the psychological mechanisms that influence purchasing decisions. By applying theoretical frameworks like signalling theory and consumer motivation theory, this research adds depth to the academic discourse on e-commerce. Furthermore, it provides a foundation for future studies to explore emerging trends and technologies in digital commerce, such as artificial intelligence in live streaming and cross-border live-streaming platforms. This contribution is essential for scholars seeking to understand the evolving dynamics of consumer behaviour in the digital age (Luo, Lim, Cheah, Lim, & Dwivedi, 2023).

Moreover, this study provides valuable recommendations for policymakers and platform designers by identifying the mechanisms that influence consumer engagement and purchasing intention in live-streaming commerce. Policymakers can use these insights to develop regulations that ensure consumer rights, ethical advertising practices, and data transparency in live-streaming environments. For platform designers, the findings highlight the importance of integrating trust-building features, such as verified reviews, real-time Q&A sessions, and personalized recommendations, to foster consumer confidence. Additionally, the research encourages platforms to adopt inclusive design principles that cater to diverse consumer groups, thereby expanding their reach and enhancing user satisfaction. These contributions are crucial for creating a live-streaming ecosystem that balances profitability with ethical responsibility (Luo, Lim, Cheah, Lim, & Dwivedi, 2023).

CHAPTER 2 LITERATURE REVIEWS

2.0 Chapter Overview

This chapter will go in deep of literature review on journals, articles and theories related on previous chapter. In this chapter, it will include the theories that applicable for the research title and objectives. By develop and building the independent variable and dependent variable, I will design a framework that suitable for this business research.

2.1 Underlying Theories

2.1.1 Consumer Buying Behaviour / Buyer's Black Box

Consumer buying behaviour encompasses the systematic evaluation, acquisition, and utilisation of goods and services to fulfil perceived needs (Madhavan & Chandrasekar, 2015). This phenomenon involves multifaceted processes shaped by an interplay of determinants, including contextual specificities, individual characteristics, and external variables (Madhavan & Chandrasekar, 2015).

These factors collectively define a consumer's identity, while simultaneously governing their decision-making frameworks, habitual purchasing patterns, brand affiliations, and retail channel preferences (Ramya & Mohamed Ali, 2016). A comprehensive analysis of these influences is critical to decoding the mechanisms driving consumption choices (Ramya & Mohamed Ali, 2016).

2.1.1.1 Psychological Factor

Motivation constitutes an innate drive that propels individuals to pursue need fulfilment, manifesting as purchasing motives when satisfaction is attained through transactional behaviour variables (Madhavan & Chandrasekar, 2015). Rooted in latent psychological or physiological tensions, motivation operates as an endogenous catalyst that activates goal-directed consumer actions (Ramya & Mohamed Ali, 2016). This construct bifurcates into

biogenic needs (physiological imperatives such as sustenance) and psychogenic needs (aspirational demands like social validation), both escalating in salience until achieving motive status—a threshold where latent needs transition into actionable intent (Roy & Datta, 2022). As a critical determinant of consumer decision-making, motivation's hierarchical interplay between core and secondary needs necessitates strategic alignment in market positioning (Qazzafi, 2020).

Perception, extending beyond the traditional five-sensory paradigm, integrates neurocognitive processes involving spatial orientation, equilibrium, and environmental awareness (Roy & Datta, 2022). To mitigate informational overload, the brain employs selective filtration mechanisms, constructing a fragmented yet functional representation of reality (TK & Sai Om Publications, 2014). This cognitive reconstruction—mediated by subjective frameworks, categorical heuristics, attentional selectivity, anticipatory biases, and experiential memory—forms a perceptual schema that guides product evaluations (Qazzafi, 2020). For instance, consumers operationalise quality assessments through symbolic cues: price and brand equity serve as primary quality proxies, while retailer credibility functions as a secondary validator (Ramya & Mohamed Ali, 2016). Such perceptual shortcuts, inherently shaped by neural mapping processes, underscore the non-rational dimensions of consumption behaviour (TK & Sai Om Publications, 2014).

2.1.1.2 Social Factor

Social factors constitute a foundational pillar in consumer behaviour analysis, operating through interconnected relational ecosystems that govern normative compliance and identity construction (TK & Sai Om Publications, 2014). As inherently communal entities, humans exhibit behavioural patterns, preference formations, and consumption choices deeply embedded in socio-environmental validation mechanisms (B Gajjar, 2013). This manifests through three institutionalised vectors: familial structures, reference group dynamics, and role-status codification—each exerting distinct yet synergistic influences on purchasing ecosystems (Al Shishani, 2020).

The familial unit operates as a primary acculturation agent, bifurcated into nuclear (individual-centric decision hierarchies) and joint (collectivised consensus models) typologies (Al Shishani, 2020). Its dual influence mechanism encompasses: 1) longitudinal value internalisation

shaping cognitive frameworks, and 2) transactional impact on purchase deliberation processes (Kavitha et al., 2023). Marketing architectures must therefore adopt household typology segmentation to address divergent demand matrices.

Besides, reference groups, function as behavioural benchmarks through mimetic isomorphism (Modi & Jhulka, 2012). These dynamically overlapping clusters (kin networks, peer cohorts, digital communities) enable both direct observational learning and indirect aspirational alignment, necessitating neuromarketing strategies that leverage social proof heuristics (Modi & Jhulka, 2012).

Concurrently, role-status congruence dictates symbolic consumption patterns. Within multi-group affiliations (professional bodies, leisure collectives), individuals curate product portfolios that performatively signal role mastery and status claims (PEREIRA et al., 2010). This semiotic consumption necessitates brand semiology frameworks where products serve as social syntax, requiring marketers to engineer culturally resonant status signifiers (PEREIRA et al., 2010).

2.1.1.3 Cultural Factor

Cultural factors function as meta-determinants in consumer behaviour, operating through institutionalized enculturation processes that shape socio-cognitive frameworks (Nayeem, 2012). Consumption paradigms emerge from value internalization mechanisms embedded within familial ecosystems and macro-social institutions, crystallizing constructs such as achievement orientation, utilitarian pragmatism, and autonomy valuation (Nayeem, 2012). These foundational schemata establish behavioural norms that guide consumption choices (Yakup et al., 2011). Therefore, marketers must prioritize cultural imprinting strategies, aligning brands with entrenched symbolic systems rather than contesting hegemonic norms, to leverage this stability (Yakup et al., 2011).

Subcultural stratification further complicates cultural homogeneity (Kire & RajKumar, 2017). Ethno-geographic, confessional, or demographic subdivisions generate normative divergences, such as consumptive taboos or lifestyle archetypes, necessitating hyper-localized market segmentation (Kire & RajKumar, 2017). These demand semiotic fluency to decode transient

symbols and aspirations, requiring adaptive strategies that balance cultural preservation with subcultural innovation (Kire & RajKumar, 2017).

Socio-economic stratification adds another layer of complexity (S Minchekar & D Mangore, 2022). Hierarchical consumption patterns reveal class-specific behaviours: elite cohorts engage in Veblen Esque conspicuous consumption to demarcate status, middle strata exhibit deliberative decision-making to maximize utility, and lower tiers demonstrate hyper localized purchasing driven by acute price sensitivity (Akdoğan et al., 2021). This tripartite structure mandates differentiated marketing architectures—from luxury brand mythmaking that amplifies exclusivity narratives to sachet marketing innovations addressing accessibility constraints (Akdoğan et al., 2021).

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2.1.1.4 Economic Factor

Economic factors serve as systemic determinants of consumer resource allocation, operating through interconnected fiscal mechanisms that regulate consumption elasticity (Zhiming, 2024). These variables—spanning personal income stratification, household earning aggregates, anticipatory income projections, liquidity buffers, and credit accessibility—collectively define expenditure propensity across market tiers (Olarenwaju, 2023). Disposable income (post-tax residuals) and discretionary income (post-necessity surplus) function as dual levers: the former governs baseline consumption of essential commodities, while the latter enables aspirational purchasing in luxury and experiential sectors (Olarenwaju, 2023). Household income composites further amplify this dynamic, dictating access to premium product categories including durable goods and status-conferring items (Olarenwaju, 2023).

Moreover, forward-looking income optimism stimulates cyclical investment in big-ticket purchases and premiumization trends, whereas pessimistic forecasts trigger defensive consumption patterns prioritizing staple goods (Madhavan & Chandrasekar, 2015). Concurrently, liquidity reserves (savings and liquid assets) modulate risk-adjusted spending thresholds—abundant reserves permit comfort-driven consumption, while constrained liquidity enforces strict budgetary rationing (Madhavan & Chandrasekar, 2015).

Next, instalment financing models and lease-to-own frameworks democratize access to capital-intensive acquisitions, effectively altering perceived affordability ceilings (Al Shishani, 2020).

Macroeconomic volatility—manifested through inflationary pressures and business cycle oscillations—imposes structural constraints, compelling consumers to recalibrate basket compositions toward inelastic goods during contractionary phases (Al Shishani, 2020).

2.1.2 Social Media Marketing

In the changing marketing context, the role of the Internet and the developments around the social media become crucial. For marketing strategists, the message is simple, understanding the role of technology in shaping the marketplace and more importantly engaging the social media as part of the marketing toolbox becomes a strategic imperative.

2.1.2.1 Social Media Marketing Conceptualization

Social media constitutes digitally mediated participatory ecosystems where users co-create, disseminate, and interact with User-Generated Content (UGC) across polymorphic interfaces including blogs, wikis, and microblogs (M. Kaplan & Haenlein, 2010).

Felix, one of the authors reconceptualized Social Media Marketing (SMM) through a four-dimensional strategic matrix—spanning operational scope (defender-explorer continuum), cultural orientation (conservatism-modernism spectrum), structural configuration (hierarchical-network paradigms), and governance models (autocratic-anarchic approaches)—establishing a systemic framework for SMM architecture (Felix et al., 2017). This paradigm positions SMM as a value co-creation nexus where organizations and consumers collaboratively ideate, curate content, and cultivate brand advocacy networks, operationalizing core tenets of relationship marketing through digitally native engagement mechanics (Filo et al., 2015).

Academic discourse bifurcates SMM conceptualizations: functionalist perspectives frame it as an omnichannel engagement platform bridging extant and latent consumer segments, while instrumentalist views prioritize its efficacy in advancing enterprise KPIs—notably consumer equity augmentation, loyalty fortification, and purchase funnel optimization (Vinerean, 2017; Yadav & Rahman, 2017; Choi et al., 2015). Simona Vinerean theorized dialogic interactivity as SMM's linchpin mechanism, wherein user-generated discourse amplifies promotional

message penetration while fostering brand-consumer symbiosis through experiential knowledge transfer (Vinerean, 2017).

The platform's dyadic utility manifests through consumer empowerment and organizational intelligence (H.M. Pham & S. Gammoh, 2015). Consumers harness SMM for brand parley, voice-of-customer articulation, and decision journey facilitation (search-evaluate-purchase), whereas enterprises leverage it for precision targeting, real-time sentiment analytics, customer lifetime value optimization via acquisition-retention synergies, and conversion-driven activations (H.M. Pham & S. Gammoh, 2015). This bidirectional value proposition underscores SMM's role as both social listening apparatus and revenue architecture in contemporary marketing ecosystems (Vinerean, 2017).

2.1.2.2 Impact of E-Word-of-Mouth on Social Media Marketing

Social media platforms facilitate a dynamic ecosystem where extant customers disseminate brand experience narratives, exerting peer influence on prospective consumers' purchase deliberations (Wang & Kim, 2017).

Concurrently, corporations harness these digital ethnographies through social listening mechanisms, enabling real-time strategic recalibration of marketing architectures (S. Coulter & Roggeveen, 2012). This paradigm shift amplifies electronic word-of-mouth's (eWOM) strategic primacy over traditional interpersonal exchanges, given its capacity for exponential reach and cognitive imprinting on brand perceptions within networked communities (S. Coulter & Roggeveen, 2012).

Moreover, empirical substantiation by (Abdallah Alalwan et al., 2017) quantifies eWOM's amplified velocity and penetrative efficacy relative to conventional marketing instruments. While another researcher establishes brand relationship quality (BRQ) as a pivotal moderator variable linking SMM investments to behavioural outcomes—particularly eWOM propagation (Hudson et al., 2016). The operational imperative thus centres on engineered UGC syndication: strategically incentivizing consumer co-creation through promoted post ecosystems and participatory campaign frameworks (Hudson et al., 2016).

2.1.3 Consumer Engagement

Customer engagement has been conceptualized through dual theoretical lenses in academic discourse: psychological predisposition and behavioural manifestation (Hu & S. Chaudhry, 2020). The psychological paradigm posits engagement as a psycho-cognitive state emerging from customers' pursuit of Maslowian higher-order needs (e.g., esteem, self-actualization) during transactional journeys, characterized by affective-cognitive brand relationship formation (Zhang et al., 2017).

Contrastingly, the behavioural school frames engagement as role-constructing participation within service ecosystems—encompassing co-design of service blueprints and resource infusion throughout service value chains (J. Brodie et al., 2011). This operational perspective is exemplified by (J. Brodie et al., 2011) conceptualization of engagement as context-bound, co-creative dyadic processes, and resource-based quantification of customer inputs during service orchestration (Hsieh & Yen, 2006).

Within livestream commerce contexts, engagement manifests as a behavioural spectrum spanning transactional acts (purchases) and non-transactional participation such as experience sharing, real-time barrage interactions and product co-evaluation (Tsai & Bagozzi, 2014). This bifurcation acknowledges engagement's polymorphic nature—serving simultaneously as conversion driver and community-building mechanism through platform-native interactivity features (Guo et al., 2021).

2.2 Reviews of Variables

2.2.1 Independent Variables

2.2.1.1 Consumer Engagement

Customer engagement has emerged as a multidisciplinary construct of significant scholarly interest across marketing, organizational behaviour, consumer behaviour, and service management domains (Kumar et al., 2010; Van Doorn et al., 2010; Vivek et al., 2014). Grounded in behavioural theory, Van Doorn et al. (2010) conceptualize engagement as a post-

transactional phenomenon encompassing customer-initiated activities centred on brands or organizations, distinct from mere purchase acts.

Complementing this, Pansari and Kumar (2017) adopt an outcome-oriented lens, defining engagement as "the value-creation mechanism through which customers contribute to organizational outcomes via direct/indirect resource investments." Operationally, this manifests as a behavioural repertoire on social media—liking, commenting, sharing, and co-creating user-generated content (UGC) in response to brand stimuli (Pansari & Kumar, 2017).

Besides, the advent of Service-Dominant (S-D) logic has further enriched this conceptual terrain (Hollebeek et al., 2019). Hollebeek et al. (2019) reconceptualize engagement as "multidimensional resource deployment (cognitive, emotional, behavioural, social) during brand interactions," emphasizing its role in value co-creation ecosystems. Concurrently, digital transformation—propelled by internet technologies—has precipitated role reconfigurations in engagement dyads, necessitating theoretical frameworks that reconcile traditional marketing paradigms with algorithm-mediated interaction architectures (Barari et al., 2020). This dual imperative—conceptual precision and operational adaptability—underscores the criticality of developing engagement models that bridge legacy and emergent marketing ontologies (Barari et al., 2020).

In this study, consumer engagement defines the as the actions that consumer willing to contribute during the live-streaming commerce activities.

2.2.1.2 Live Host Characteristics

Live streamers constitute a transformative agent in digital commerce, operationalizing real-time video platforms to orchestrate product exhibitions and experiential narratives that bridge information asymmetries inherent in static e-commerce formats m (XIE et al., 2019). Through synchronous interactivity and performative product dramaturgy, they reconfigure the consumption journey by augmenting informational completeness and hedonic value—a paradigm shifts empirically validated by XIE et al. (2019). This modality outperforms offline retail guidance in transactional efficiency, capitalizing on the trust economy cultivated through quality assurance and value optimization strategies (Dong et al., 2019).

Next, theoretical constructs position live streamers as hybridized social actors synthesizing influencer charisma and opinion leadership attributes (Dong et al., 2019). Their competency matrix encompasses four axial dimensions: physical attractiveness (visuo-aesthetic capital), entertainment quotient (affective engagement mechanics), domain expertise (product mastery), and dialogic interactivity (bidirectional communication fluency) (Liu et al., 2020). Of these, attractiveness emerges as a polyvalent construct—simultaneously encoding phenotypic traits, parasocial affinity, and task-efficacy signalling—that live streamers weaponize through high-frequency persuasive rhetoric to engineer pleasure-infused shopping rituals (Han & Xu, 2020).

Moreover, attractiveness operates as a tripartite decision catalyst, particularly salient in appearance-contingent consumption contexts (McColl & Truong, 2013). Its constitutive dimensions—physiological allure (somatic capital), personality magnetism (relational capital), and competence credibility (performance capital)—function as trust heuristics under Knightian uncertainty. Streamers mastering this trifecta achieve superior trust-to-conversion ratios, as per source credibility frameworks and digital influencer efficacy models (Chekima et al., 2018).

Therefore, in this study, live-streaming characteristics will define as whether the characteristics shown by live-streamer will affect the purchasing intention of customer in live-streaming commerce.

2.2.1.3 Information Quality

Informational Value operationalizes consumers' pursuit of cognitively salient, temporally relevant, and source-specific data to optimize purchase (Zamzuri et al., 2018). Chandon et al. (2000) conceptualize it as a utilitarian construct delivering instrumental utilities—non-hedonic benefits that cognitively scaffold decision architecture through product/service intelligence. This value proposition manifests most acutely during goal-directed consumption episodes, wherein informationally dense messaging triggers pre-purchase search behaviours and evaluative processing (Zamzuri et al., 2018).

Besides, product fit uncertainty—a cognitive state stemming from informational asymmetries in digital environments—demands resolution through enhanced product ontologies. C. Liu and Arnett (2000) posit that e-commerce platforms mitigating this uncertainty via granular product disclosures enable consumers to achieve need-product congruence with minimized cognitive

load. This aligns with Childers et al. (2001) efficiency paradigm, reframing informational value as a time-optimized path to purchase through semantic relevance filtering.

On the other hand, the strategic curation of informational assets exerts measurable impacts on consideration sets. Sautter et al. (2004) demonstrate that utility-maximizing content elevates product quality diagnostic, while Çelik and Yılmaz (2011) identify accuracy and actionability as meta-criteria shaping digital decision journeys. Contemporary operationalizations prioritize embedded decision scaffolds—ratings, UGC reviews, algorithmic recommendations—that transform raw data into choice heuristics (Li, 2019).

Then, in this study, information quality defined as the quality and the presentation methods of products or service's information provide in live-streaming commerce activities.

2.2.1.4 Time- Scarcity

Time scarcity encapsulates the temporal resource misalignment wherein task completion demands exceed available temporal bandwidth (X. S. Liu et al., 2022). As a strategic behavioural nudge, Song et al. (2019) operationalize this construct across digital consumption ecosystems—leveraging countdown mechanics in reservation systems, urgency framing in seasonal campaigns, and perishable inventory cues in experiential purchases (C. Li et al., 2021).

Empirical evidence reveals a temporal elasticity paradox: extended browsing durations foster deferred impulse conversion through cognitive deliberation (C. Li et al., 2021), whereas acute temporal constraints amplify perceived value via scarcity heuristics, triggering immediate compulsive consumption (Wu et al., 2021). This bifacial impact underscores the context-dependent modulation of time scarcity on impulsive decision architectures (Wu et al., 2021).

Live-streaming commerce (LSC) distinctively reconfigures temporal dynamics relative to social commerce and brick-and-mortar paradigms. Its ephemeral consumption windows engineer artificial temporal ceilings that hyper-charge purchase immediacy (Peng et al., 2019). The platform's inherent tempo acceleration and consumers' heightened chronemic sensitivity coalesce into a high-velocity decision ecosystem where microseconds modulate conversion probabilities (S. Zhang et al., 2022).

In conclusion, the time-scarcity defined as the time duration of live-streaming commerce is limiting the time duration of consumer making decisions.

2.2.2 Dependent Variable – Purchase Intention

Purchase intention represents a cognitive-behavioural construct that examines consumers' predisposition toward brand-specific procurement rationales (Shah et al., 2012). Shah et al. (2012) also operationalize it as a conditional propensity wherein situational variables activate product acquisition tendencies. The consumer decision journey constitutes a nonlinear psychosocial process, with purchase intention emerging as a composite function of behavioural schemata, perceptual filters, and attitudinal vectors (Shah et al., 2012).

This intention-behaviour nexus operates through multilevel cognitive architecture. Purchase intention serves as the primary antecedent variable in consumption ecosystems, enabling marketers to model decision trajectories through behavioural econometrics (Gogoi, 2013). Its plasticity is evidenced through dynamic recalibrations triggered by price elasticity, perceived quality gradients, and value proposition revaluations.

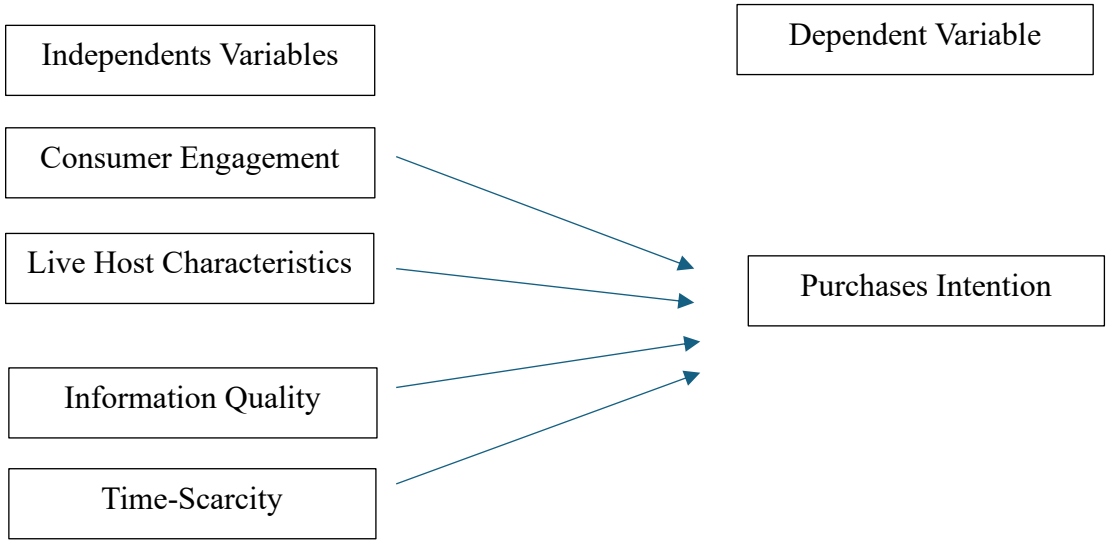
Besides, during the consumer’s purchasing flow, the purchase pathway is theoretically segmented into six sequential yet recursive phases: cognitive awakening → informational encoding → affective engagement → preferential crystallization → persuasive reinforcement → transactional execution (Kawa et al., 2013).

In short, the purchase intention is defined as the disposition the customer presents to acquire a product and/or service and the probability of this to be effectively purchased.

2.3 Proposed Research Framework

2.3.1 Conceptual Research Framework

Figure 2.1 Conceptual Research Framework



2.4 Hypothesis Development

2.4.1 Consumer Engagement and Purchases Intention

Customer engagement has been established as a critical success factor in social commerce ecosystems, functioning as both a behavioural driver and relational catalyst (Kim et al., 2017). Empirical studies confirm its mediating role in converting social interactions into purchase intent, particularly through community-based value co-creation (Prentice et al., 2019). The ascendancy of livestream commerce—a hybrid channel merging high-touch interactivity with information density—has redefined retail engagement paradigms. Retailers now leverage its synchronous, multi-sensory interfaces to orchestrate immersive shopping rituals (Xu & Nuangjamnong, 2022).

Moreover, Yu and Zheng (2022) theorize that sustained engagement fosters brand community embeddedness—a state of cognitive-emotional interdependence where consumers internalize brand narratives. This embeddedness manifests as a self-reinforcing loop: community participation → brand identity internalization → purchase of brand-associated offerings (Xu & Nuangjamnong, 2022). Sun et al. (2019) further quantify this dynamic in livestream contexts, demonstrating a relationship between engagement intensity and impulse purchase likelihood—a relationship amplified by real-time social proof dynamics.

Therefore, based on the research and reviews, the hypothesis will be:

H1: Customer engagement has a significant influence on purchase intention

2.4.2 Live Host Characteristics and Purchases Intention

Research confirms that physical attractiveness significantly shapes perceptions and interactions. Individuals with greater aesthetic appeal are consistently perceived as more likable, socially skilled, and psychologically stable compared to less attractive counterparts (McColl & Truong, 2013). Attractive sales professionals are regarded as more persuasive, leveraging their visual appeal to amplify influence over consumer decisions (McColl & Truong, 2013).

Personality traits—including extroversion, sincerity, and approachability—serve as critical enhancers of interpersonal appeal (Montoya et al., 2008). Extroverts excel in fostering dynamic group engagement, generating positive resonance across personality types (Sautter et al., 2004). For live streamers, these traits heighten audience attention and cultivate favourable brand perceptions (Montoya et al., 2008).

Interpersonal competence further magnifies attractiveness. Expertise and skilfulness in live broadcasters strengthen consumer trust, reliability, and emotional engagement (Dimmock et al., 2015). Studies additionally indicate that perceived attractiveness triggers emotional arousal, directly enhancing consumer evaluations and purchase intent (Dimmock et al., 2015).

Therefore, the hypothesis will be:

H2: Live host characteristics have a significant impact on purchases intention.

2.4.3 Information Quality

In this study, information quality is defined as viewers' evaluation of the accuracy, timeliness, and thoroughness of content presented in live streams (Ghasemaghaei & Hassanein, 2015). Consumer decisions are anchored in the information they encounter, with information quality acting as a driver of viewer behaviour that shapes purchasing choices in digital settings (Ghasemaghaei & Hassanein, 2015).

On the other hand, Kim et al. (2004) examined the relationship between online product research intent and purchase intent, identifying information-seeking behaviour as a predictor of buying decisions. Their findings emphasize that accessible product details and ease of access on e-commerce platforms heighten the likelihood of completed purchases.

Extending this insight, Chiu et al. (2010) demonstrate that information quality correlates with customer behavioural intent that including purchasing via the live-streaming commerce platform—a linkage further validated by Kim and Niehm (2009).

Concurrently, the hypothesis of this independent variable will be:

H3: Information Quality have a significant impact on purchases intention.

2.4.4 Time-Scarcity

Livestream commerce operates within fixed-duration sessions, typically spanning several hours, thereby applying temporal limitations on consumer purchasing opportunities (Park & Jang, 2018). During live-streaming commerce, the live hosts frequently employ countdown notifications during broadcasts to emphasize time-sensitive purchasing windows (H. J. Park & Lin, 2020). Phrases such as "Limited stock remaining!" or "Next product launching shortly!" serve as temporal urgency cues that motivate immediate action (Park & Jang, 2018).

Concurrently, scholarly investigations confirm that scarcity-based marketing tactics systematically alter consumer product evaluation and decision-making processes (Brannon & Brock, 2001). Real-time temporal indicators from hosts can disrupt conventional information assimilation patterns (Gong et al., 2021). The inherent time-bound structure of livestream commerce restricts consumer choice autonomy, compelling accelerated purchase resolutions (Gong et al., 2021).

Therefore, the hypothesis between the time-scarcity and purchasing intention will be:

H4: Time-Scarcity have a significant impact on purchases intention.

CHAPTER 3 METHODOLOGY

3.0 Introduction

Chapter 3 presents an overview of the methods used in this investigation. The first section discusses the research design, which details the study's methods. The next sections include data collecting, sample methods, research tools, construct evaluation, data processing, and data analysis.

3.1 Research Design

The research questions that we study in this paper are about how consumers are influenced by live streaming and streamers in their decision-making process. The framework methodology implemented herein enables the review to deliver a reliable synthesis of literature and a structured understanding of Live-Streaming Commerce (LSC) research.

3.1.1 Quantitative Research

Quantitative research methods have been described as a fundamental approach in social research. It has a focus on the numerical side of data, which can be quantified and analysed through statistical analysis to provide and support claims, which in turn generalises findings and explains phenomena.

There are various advantages to using quantitative research, which include utilising statistics to generalise findings, which in turn can provide explanations for past, current, and future events. Quantitative methods are best used when research is involved with quantifying findings to provide accurate outcomes such as measuring population.

Considering the scope of this research, there is a broad range of questions that need to be asked. This makes quantitative methods a beneficial choice for the data collection stage, as they can measure variances or test a hypothesis for reasoning behind an occurrence. While the origins of quantitative research do not embody the same degree of philosophical and paradigmatic

diversity as qualitative does, it holds a plethora of approaches whether they are exploring, describing, or explaining.

3.2 Sampling Design

3.2.1 Target Population

Undergraduate students enrolled in a variety of courses at Klang Valley higher education institutions make up the study's target group. Therefore, the target population will be focus on the foundation, undergraduate, postgraduate students that study in University Tunku Abdul Rahman. It will be more effective and efficiency to go through the survey process within a specific area and will present a more likely behaviour and habits of activities during the survey process.

3.2.2 Sampling Frame

An essential research instrument for the methodical identification and selection of possible research participants is a sampling frame. Creating a strong sampling frame was essential to guaranteeing the representativeness of the sample in our survey of undergraduate students in University Tunku Abdul Rahman.

Our study relies heavily on this group, thus a thorough grasp of it is essential. It is essential to define and comprehend this group in order to establish a foundation for significant and pertinent educational study. With the ultimate goal of advancing higher education locally, we aim to learn more about the experiences, difficulties, and ambitions of these students.

3.2.3 Sampling Methods

This study employs a non-probability sampling technique, specifically judgmental sampling, to select participants based on prior knowledge and professional judgment. The key advantage of judgmental sampling is its ability to directly target the desired audience, enabling efficient access to relevant respondents. Before conducting the survey or research, the researcher will screen participants by confirming their usage of social media and participation of live-

streaming commerce and activities by online platform. This careful pre-selection ensures that the chosen participants align with the research objectives and increases the likelihood of obtaining accurate and relevant insights.

3.2.4 Sampling Size

When determining sample size, several factors must be considered, including the size, diversity, and distribution of the target population. A sufficiently large random sample is essential to ensure unbiased results and minimize sampling errors, enabling generalization of findings. The adequacy of the sample size depends on the complexity of the population, research objectives, and the chosen quantitative analysis method rather than the specific proportion of the population being sampled.

While larger sample sizes generally reduce the likelihood of bias and sampling errors, this effect tends to diminish after reaching a certain threshold. However, it is important to balance the sample size with available research resources. Statistical formulas can assist in calculating the appropriate sample size for a study, taking these factors into account.

In this study, 200 undergraduate students from University Tunku Abdul Rahman in Sungai Long campus will be surveyed through online form. This sample size is considered adequate to represent the overall population, ensuring both reliability and validity in the research findings.

3.3 Data Collection Methods

Primary data refers to information collected directly to address a specific research problem. This type of data can be gathered through various methods and is typically regarded as more reliable and valid. Since it is obtained directly from the original source, primary data offers first-hand insights that are highly relevant and tailored to the research objectives.

For this study, a quantitative approach was employed to collect primary data. The questionnaires were generated using Google Forms and disseminated through various social media channels, including WhatsApp Messenger and email.

Before the final collection of data, this study will conduct a pre-test of the designed survey in a small and particular group, its is to clarify to ensure the survey is reliable and without any mistake. After the pre-test, it will run out the final online survey form to start collect the data that intend to use for the further study.

Moreover, to verify the correct target population, the survey form will require a university email to login before filling it, but this Google forms does not collect the respondent email, which means respondents can submit their answers without providing any critical personal information. This addresses most people's concerns about privacy protection and can increase their willingness to participate.

3.3.1 Questionnaires Design

The questionnaire, written in English, consists of three sections: Pre-screening, Section A, and Section B. The pre-screening section includes a single question designed to confirm participants' eligibility before allowing them to proceed to the next parts of the questionnaire.

Section A will then gather demographic information from participants, including age, gender, race, and social media usage experiences. Section B to E will focus on participants' responses to the independent variables such as consumer engagement, live-host characteristics, information quality and time-scarcity. Last, the section F will conduct the research's dependent variable (purchasing intention).

In addition, Pre-screening and Section A will be asked in the form of Multiple-Choice Questions, while Section B to F will employ a Five-Point Likert Scale, ranging from strongly disagree to strongly agree, for participants to rate their responses.

3.3.2 Construct of Questionnaire

Independent Variable	Items	Modified Questions	Sources
Consumer Engagement	5	I am willing to spend more time on the live streaming platform.	(Cao et al., 2022)

		I am willing to try, follow, subscribe and track the information or activities of sellers.	
		When I am using live-streaming platform to shop, I prefer to choose sellers who use live streaming.	
		I am willing to recommend/share the seller who carries the live streaming to my friends/relatives.	
		I am willing to encourage relatives and friends to use live shopping.	

Independent Variable	Items	Modified Questions	Sources
Live-Streaming Host Characteristics	5	I think live streaming host are familiar with the product and have professional knowledge, so they can explain clear and accurate activity information.	(Z. Zhang et al., 2022)
		The products recommended by interesting/funny live streaming hosts are more attracting to me.	
		The communication and interaction of the live-streaming hosts are very actively.	
		I often watch programs with funny, outward-looking, lively live streaming hosts.	
		I think the live streaming host I watch has special skills and expertise.	

Independent Variable	Items	Modified Questions	Sources
Information Quality	4	I think the live streaming commerce will provides enough rich content.	(L. Wang et al., 2024)
		I think the live streaming commerce provides complete and detailed information about the product.	
		I think the live streaming commerce provides accurate and timely information for my purchasing decisions.	
		I think the live streaming commerce platform provides comparative information between products.	

Independent Variable	Items	Modified Questions	Sources
Time-Scarcity	4	I feel that the sale time of the live streaming commerce is usually relatively short.	(Wang, Zhang, & Zhang, 2024)
		I feel like I'm rushing to grab deals just before the deadline.	
		I am worried about the products will be sold out during a limited time in live streaming.	
		When the live streaming is almost ended, I feel pressure to make my decisions	

Dependent Variable	Items	Modified Questions	Sources
Purchasing Intention	4	I am probably going to buy the products on this live streaming commerce platform.	(Z. Zhang et al., 2022)
		When I watch the livestream of e-commerce, I often buy something that I didn't intend to buy.	
		When I watch the live commerce, I often find some goods I want to buy that are rarely used	
		When I see the live streaming host is recommending a product, I immediately want to own it	

3.4 Data Analysis Tools

The computer software that will be used to analysis the data is IBM SPSS. IBM SPSS is a tool to compute statistical power analyses for many data types such as multi linear regression, ANOVA and reliability test. Besides, IBM SPSS can also be used to compute effect sizes and to display using arranged table results of power analyses.

3.4.1 Descriptive Analysis

Descriptive analysis is a sort of data research that aids in describing, demonstrating, or helpfully summarizing data points so those patterns may develop that satisfy all of the conditions of the data. The most popular descriptive work tools are simple statistics representing core trends and variations (such as means, medians, and modes), which may be highly useful for explaining data.

Besides, a reliability test evaluates the consistency and dependability of measurement tools (e.g., surveys, scales, or data collection instruments) to ensure they produce stable and repeatable results. It assesses whether a metric or instrument consistently measures a construct (e.g., customer satisfaction, brand loyalty) across time, contexts, or raters, minimizing random error. Common methods include Cronbach's alpha ($\alpha \geq 0.7$), test-retest reliability, and inter-rater reliability.

Then, after collecting the survey, this study will analyse the demographic of respondents such as income group, frequency of usage in social media, it may state the habits and the background of respondents attend in the live streaming commerce.

3.4.2 Inferential Analysis

Inferential statistics are often used to compare the differences between the treatment groups. Inferential statistics use measurements from the sample of subjects in the experiment to compare the treatment groups and generalize about the larger population of subjects.

There are many types of inferential statistics and each is appropriate for a specific research design and sample characteristics. Researchers should consult the numerous texts on experimental design and statistics to find the right statistical test for their experiment.

3.4.2.1 Multiple Regression Analysis

Multiple Linear Regression, or multiple regression, is a statistical method that employs multiple predictor variables to forecast the value of an outcome variable. Multiple Linear Regression aims to quantify the linear association between independent variables (predictors) and a dependent variable (target metric).

Formula and Calculation of Multiple Linear Regression (MLR)

$PI=\beta0+\beta1(CE)+\beta2(LC)+ \beta3(IQ)+\beta4(TS)+\epsilon$

where:

PI = Purchasing Intention (dependent variable)

$\beta0$ = y intercept (constant term)

$\beta 1(CE)$ = slope coefficients for Consumer Engagement (independent variable)

$\beta 2(LC)$ = slope coefficients for Live Streaming Host Characteristic (independent variable)

$\beta 3(IQ)$ = slope coefficients for Information Quality (independent variable)

$\beta 4(TS)$ = slope coefficients for Time-Scarcity (independent variable)

ϵ = The model's error term

The independent variables are parameters used to estimate the dependent variable's value. Multiple Linear Regression expands upon simple regression by incorporating multiple predictors. The coefficient of determination (R-squared) measures the proportion of variance in the dependent variable explainable by the independent variables. Notably, R^2 invariably increases with additional predictors—even irrelevant ones—compromising its utility for predictor selection. R^2 ranges from 0 (no predictive power) to 1 (perfect prediction) but cannot independently validate predictor relevance.

During the interpretation of Multiple Linear Regression, beta coefficients reflect each predictor's marginal effect when other variables are held constant. Results may be presented as a regression equation or summarized in coefficient tables.

3.4.2.2 ANOVA

Analysis of Variance (ANOVA) is a foundational statistical technique in business research designed to evaluate whether there are statistically significant differences in the means of three or more independent groups. By partitioning observed variance into systematic (explained) and random (unexplained) components, ANOVA determines if variations in a dependent variable (e.g., sales revenue, customer satisfaction scores) are attributable to specific categorical factors (e.g., marketing campaigns, geographic regions, product lines) or random fluctuations.

The method tests the null hypothesis (H_0) that all group means are equal against the alternative hypothesis (H_1) that at least one group differs significantly. Central to ANOVA is the F-statistic, calculated as the ratio of between-group variance to within-group variance, where a higher F-value indicates greater divergence among group means relative to internal variability. Statistical significance is typically assessed using a p-value threshold (e.g., $p < 0.05$), with results guiding strategic decisions such as optimizing resource allocation or refining operational tactics. Common variants include One-Way ANOVA and Two-Way ANOVA. In this study, it will

conduct a Two-Way ANOVA to test the relationship between each independent variables with the dependent variable.

For valid interpretation, ANOVA assumes homogeneity of variances, normality of residuals, and independence of observations. For instance, a multinational corporation might apply One-Way ANOVA to assess whether customer retention rates differ significantly across its four pricing tiers, thereby informing tier-specific retention strategies.

3.4.2.3 Coefficients Analysis

Coefficients analysis in business research involves interpreting regression coefficients to quantify the directional and magnitude relationships between dependent variable and independent variables. Each coefficient estimates the expected change in the outcome per unit change in a predictor, assuming other variables remain constant.

A critical aspect of this analysis is evaluating multicollinearity—when predictors are highly correlated—using collinearity tolerance and the Variance Inflation Factor (VIF). Collinearity tolerance measures the proportion of a predictor's variance not explained by others in the model (calculated as 1−R21−*R*2, where R2*R*2 is derived from regressing one predictor against others). Tolerance values below 0.1–0.2 signal problematic multicollinearity.

Next, VIF, the reciprocal of tolerance (VIF=1/Tolerance), quantifies how much a predictor's standard error is inflated due to collinearity. VIF thresholds above 10 indicate severe multicollinearity, which distorts coefficient stability and significance tests.

CHAPTER 4 DATA ANALYSIS

4.0 Introduction

About this chapter, it will focus on analysis the data collected from the selected sample through online survey form. Besides, after analysis, this chapter will also interpret the analysed data.

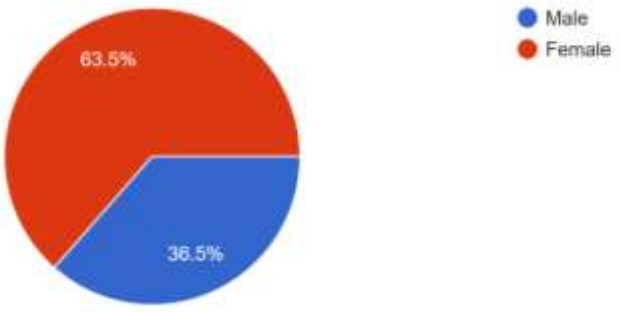
4.1 Descriptive Analysis

In this part, it will present the analysis of the demographic characteristics of the respondents based on frequency and percentage analysis. Besides. It will present the data collected from section b to f, analysis a descriptive statistic and present an interpretation of the descriptive statistics.

4.1.1 Demographics Analysis

4.1.1.1 Respondent's Gender

Figure 4.1: Descriptive Analysis for Gender



Source: Developed for the research

Table 4.1: Descriptive Analysis for Gender

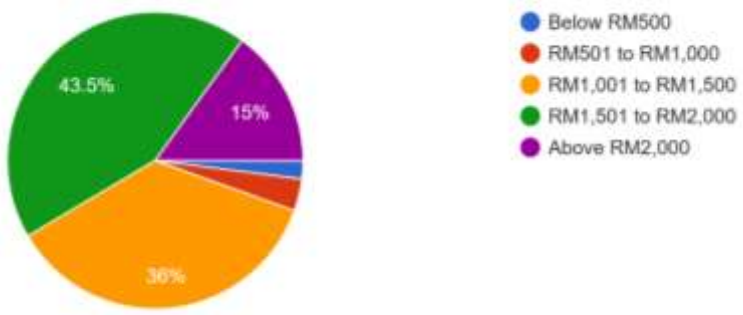
		FREQUENCY	PERCENT	VALID PERCENT	CUMULATIVE PERCENT
VALID	Female	127	63.50	63.50	63.50
	Male	73	36.50	36.50	100.00
	Total	200	100.00	100.00	

Source: Developed for the research

According to the table 4.1 and figure 4.1, this research collected 200 responses which consist of 73 (36.50%) of responders are. Besides, males 127 (63.50%) females, which is already more than the average number of respondents.

4.1.1.2 Respondent's Monthly Income/Allowance

Figure 4.2: Descriptive Analysis for Monthly Income/Allowance



Source: Developed for the research

Table 4.2: Descriptive Analysis Monthly Income/Allowance

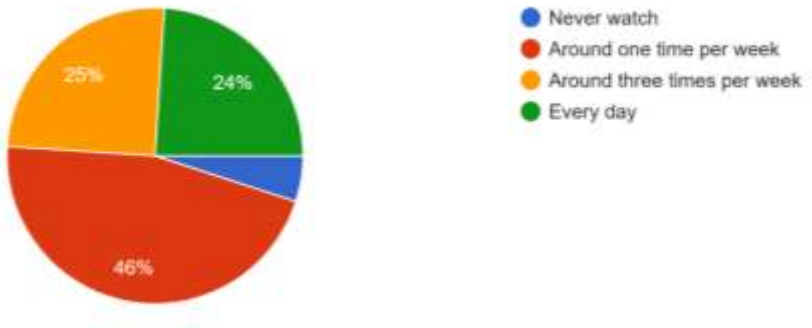
		FREQUENCY	PERCENT	VALID PERCENT	CUMULATIVE PERCENT
VALID	Below RM500	4	2	2	2
	RM501 to RM1,000	7	3.50	3.50	5.50
	RM1,001 to RM1,500	72	36	36	41.50
	RM1,501 to RM2,000	87	43.5	43.5	85
	Above RM2,000	30	15	15	100.00
	Total	200	100.00	100.00	

Source: Developed for the research

According to table 4.2 and figure 4.2 show the data of the monthly incomes or allowances of respondents, the distribution shows a clear concentration pattern. Middle-to-high income groups (RM1,001 to RM2,000) dominate overwhelmingly, accounting for 79.50% of the total (36% in RM1,001-RM1,500 and 43.5% in RM1,501-RM2,000). The largest segment is RM1,501 to RM2,000, covering 87 people (43.50%). Meanwhile, the high-income group above RM2,000 represents 15% (30 people), while the low-income population (below RM1,000) is minimal at 5.50% (2% below RM500 and 3.50% in RM501-RM1,000). Cumulative percentages reveal that 85% of respondents earn below RM2,000 monthly, and those earning below RM1,500 account for 41.50%.

4.1.1.3 Respondent's Time Spent on Live-Streaming Commerce

Figure 4.3: Descriptive Analysis for Time Spent on Live-Streaming Commerce



Source: Developed for the research

Table 4.3: Descriptive Analysis for Time Spent on Live-Streaming Commerce

		FREQUENCY	PERCENT	VALID PERCENT	CUMULATIVE PERCENT
VALID	Never watch	10	5	5	5
	Around one time per week	92	46	46	51
	Around three times per week	50	25	25	76
	Every day	48	24	24	100

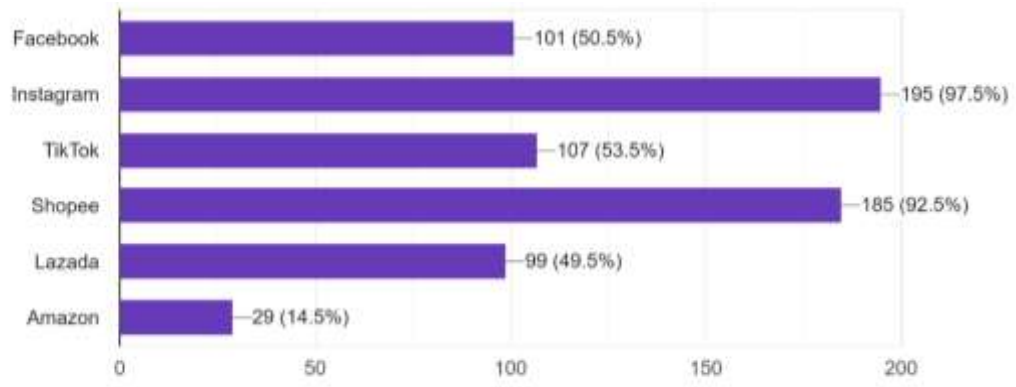
	Total	200	100	100

Source: Developed for the research

Figure 4.3 and table 4.3 shown the time spent on live-streaming commerce of respondents. The highest proportion (46%, 92 people) watch live-streaming commerce around once weekly, while 25% (50 people) participate about three times per week and 24% (48 people) engage daily, indicating nearly half (49%) are high-frequency users (3+ times weekly). Notably, only 5% (10 people) never watch, demonstrating broad audience penetration. Cumulative percentages show 51% watch up to once weekly, and 76% engage up to three times weekly. Overall, engagement is polarized: a stable daily user base (24%) coexists with a large pool of light-to-moderate users (1-3 times weekly), while non-participants remain a tiny minority which is 10 respondents only (5%).

4.1.1.4 Respondent's Frequently Used Social Media/ Live-Streaming Commerce Platforms

Figure 4.4: Descriptive Analysis for Frequently Used Social Media/ Live-Streaming Commerce Platforms



Source: Developed for the research

Table 4.4: Descriptive Analysis for Frequently Used Social Media/ Live-Streaming Commerce Platforms

		FREQUENCY	PERCENT	VALID PERCENT
VALID	Facebook	101	50.50	50.50
	Instagram	195	97.50	97.50

	TikTok	107	53.50	53.50
	Shopee	185	92.50	92.50
	Lazada	99	49.50	49.50
	Amazon	29	14.50	14.50
	Total	716		

Source: Developed for the research

According to figure and table 4.4, The collected data shows Instagram and Shopee are the most widely used platforms, with 195 people (97.50%) and 185 people (92.50%) penetration respectively, nearing universal adoption. Following are TikTok with 107 people (53.50%) and Facebook 101 people (50.50%). Besides, Lazada is used by nearly half which is 99 people (49.50%). While Amazon ranks the lowest, 29 people only (14.50%). Lastly, the total responses (716 times) indicate most respondents are using multiple platforms simultaneously.

4.1.2 Descriptive Statistics of Constructs

Table 4.5: Descriptive Statistics of Constructs

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Consumer Engagement	200	1.20	5.00	4.0120	.84915
Live-Streaming Host Characteristics	200	1.40	5.00	3.9590	.79831
Information Quality	200	1.50	5.00	3.9850	.83374
Time-Scarcity	200	1.50	5.00	3.9475	.88879
Purchasing Intention	200	1.00	5.00	3.9738	.88872
Valid N (listwise)	200				

Source: Data generated by IBM SPSS Statistic based on survey for research

According to figure and table 4.5, it is the analysis of the data collected in section b to f with covering both independent and dependent variables. These involved the calculations of descriptive statistics or central tendency such as the mean, dispersion measures, and standard deviation. Results for each variable are presented in their own sections. One of the sections,

the mean is the most used item for measure in descriptive statistics, by using all values to provide the average between the minimum and maximum values in the data set.

All variables have a complete sample size of N=200 with no missing data. The highest mean values are observed in Consumer Engagement (4.0120) and Information Quality (3.9850), indicating strong approval of interactive experiences and content reliability in live-streaming commerce. The dependent variable Purchasing Intention (3.9738) also shows a high mean near 4 points, reflecting overall positive purchase intent. Time-Scarcity (3.9475) and Host Characteristics (3.9590) have slightly lower means but still lean toward positive evaluations. It refers to the constructs showed similar levels of agreement, with mean scores leaning slightly toward the "agree" option. Moreover, standard deviations (0.80–0.89) suggest moderate consensus among respondents.

4.1.3 Reliability Analysis

Table 4.6: Reliability Analysis

No.	Construct	Cronbach's Alpha	No. of Items	Strength of Association
1.	Consumer Engagement	0.822	5	Good
2.	Live-Streaming Host Characteristics	0.787	5	Acceptable
3.	Information Quality	0.755	4	Acceptable
4.	Time-Scarcity	0.784	4	Acceptable
5.	Purchasing Intention	0.794	4	Acceptable

Source: Data generated by IBM SPSS Statistic based on survey for research

According to table 4.6, first, in the part of independent variables, the result for Cronbach's Alpha of Consumer Engagement which is 0.822 with 5 measurement items, for Live-Streaming Host Characteristics which is 0.787 with 5 measurement items. Besides, Information Quality which is 0.755 with 4 measurement items. Next, Time-Scarcity's Cronbach's Alpha is 0.784 with 4 measurement items. Lastly, in part of dependent variable, Purchasing Intention's Cronbach's Alpha is 0.794, with 4 measurement items.

Based on the reliability test in table 4.6, the Cronbach's Alpha of each construct are passed the test, which means the measurement items in each construct is valid. The strength of association in Consumer Engagement is considered at "Good", which its alpha value is between 0.8 to 0.9. Moreover, the others 3 independent variables' alpha value (Live-Streaming Host Characteristics, Information Quality, Time-Scarcity) are between 0.7 to 0.8, which considered as "Acceptable". For the dependent variable (Purchasing Intention), its alpha value also between 0.7 to 0.8, which is considered as a "Acceptable" level.

4.2 Inferential Analysis

4.2.1 Multiple Linear Regression Analysis

Based on the inferential analysis, this chapter will using multiple linear regression analysis to analysis and provide interpretation for the survey collected. Multiple Linear Regression (MLR) is a statistical technique used to model the relationship between one dependent variable and two or more independent variables. It assumes a linear association and helps predict or explain how changes in predictors affect the outcome.

4.2.1.1 Model Summary

Table 4.7: Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.895[a]	.802	.798	.39970

a. Predictors: (Constant), TS, CE, IQ, LC

Source: Data generated by IBM SPSS Statistic based on survey for research

The model summary from the multiple linear regression analysis reveals a robust relationship between the independent variables—Consumer Engagement (CE), Live-Streaming Host Characteristics (LC), Information Quality (IQ), and Time-Scarcity (TS)—and the dependent variable Purchasing Intention. With a high multiple correlation coefficient (R = 0.895), the model demonstrates a very strong positive association between these predictors and purchasing intention, indicating that the combined influence of CE, LC, IQ, and TS explains a substantial

proportion of the variability in consumer purchase decisions. The R^2 value of 0.802 suggests that approximately 80.2% of the variance in purchasing intention is accounted for by these four factors, highlighting the model's strong explanatory power. After adjusting for the number of predictors, the Adjusted R^2 remains at 0.798, confirming that the model's performance is reliable and not artificially inflated by overfitting.

Additionally, the standard error of the estimate (0.39970) reflects a relatively small average deviation between the observed and predicted values of purchasing intention, further validating the model's precision. Overall, these results underscore the critical role of consumer engagement, host characteristics, information quality, and time-sensitive cues in shaping purchase intent within live-streaming commerce.

4.2.1.2 ANOVA

Table 4.8: ANOVA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	126.022	4	31.505	197.206	<.001[b]
	Residual	31.153	195	.160		
	Total	157.175	199			

a. Dependent Variable: PI

b. Predictors: (Constant), TS, CE, IQ, LC

Source: Data generated by IBM SPSS Statistic based on survey for research

According to the table 4.8, the ANOVA results demonstrate that the regression model is highly statistically significant ($F=197.206$, $p<.001$), indicating that the combined effect of Consumer Engagement (CE), Live-Streaming Host Characteristics (LC), Information Quality (IQ), and Time-Scarcity (TS) on Purchasing Intention is not due to random chance. The extremely low p-value (less than 0.001) rejects the null hypothesis that all regression coefficients are zero, confirming that at least one of these predictors has a significant impact on purchase intent. This underscores the collective importance of these variables in explaining consumer behaviour within live-streaming commerce contexts.

4.2.1.3 Coefficients Analysis

Table 4.9: Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.067	.149		-.448	.655		
	CE	.422	.076	.403	5.558	<.001	.193	5.182
	LC	.182	.079	.164	2.296	.023	.200	5.009
	IQ	.204	.067	.192	3.069	.002	.261	3.831
	TS	.205	.057	.205	3.616	<.001	.315	3.178

a. Dependent Variable: PI

Source: Data generated by IBM SPSS Statistic based on survey for research

Based on the table 4.9. The regression analysis identifies Consumer Engagement (CE) and Time-Scarcity (TS) as the most statistically significant predictors of Purchasing Intention (PI), both with p<.001. CE exhibits the strongest impact (B=0.422), followed by TS (B=0.205), highlighting their critical roles in driving purchase decisions. Information Quality (IQ) (p=0.002) and Live-Streaming Host Characteristics (LC) (p=.023) also show significant positive effects, though their contributions are comparatively smaller.

Next, in the unstandardized Beta, Consumer Engagement (CE) has the most substantial influence, with an unstandardized coefficient (B) of 0.422 and a standardized beta of 0.403. This indicates that a one-unit increase in CE leads to a 0.422 increase in PI, and CE is the strongest predictor in the model. Time-Scarcity (TS) contributes to PI with unstandardized Beta 0.204, Beta = 0.192, which means that an increase in one unit of Time-Scarcity will leads to a 0.204 increase in Purchasing Intention, is the second highest in this survey result.

Furthermore. Information Quality (IQ) contributes to PI with unstandardized Beta 0.204, Beta = 0.192, reflecting increase in one unit of Information Quality will leads to a 0.204 increase in Purchasing Intention. The lowest is the Live-Streaming Host Characteristics, with a unstandardized Beta 0.182, Beta 0.164, shown that an increase in one unit of Live-Streaming Host Characteristics will leads to a 0.182 increase in Purchasing Intention.

Besides, multicollinearity diagnostics confirm the reliability of these results. The Variance Inflation Factor (VIF) values for all predictors range between 3.178 (TS) and 5.182 (CE), well below the critical threshold of 10, indicating no severe multicollinearity. Tolerance values

(ranging from 0.193 to 0.315) further validate that predictor independence is maintained, ensuring robust coefficient estimates.

4.2.1.4 Pearson Correlations Analysis

Table 4.10: Pearson Correlations Analysis

Correlations

		PI	CE	LC	IQ	TS
PI	Pearson Correlation	1	.861**	.830**	.815**	.790**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001
	N	200	200	200	200	200
CE	Pearson Correlation	.861**	1	.867**	.831**	.762**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001
	N	200	200	200	200	200
LC	Pearson Correlation	.830**	.867**	1	.797**	.797**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001
	N	200	200	200	200	200
IQ	Pearson Correlation	.815**	.831**	.797**	1	.768**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001
	N	200	200	200	200	200
TS	Pearson Correlation	.790**	.762**	.797**	.768**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	
	N	200	200	200	200	200

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Data generated by IBM SPSS Statistic based on survey for research

According to table 4.10, the Pearson Correlation matrix reveals strong positive associations among all variables, particularly between the dependent variable Purchasing Intention (PI) and the independent variables. Purchasing Intention exhibits very high correlations with Consumer Engagement (CE) (r=0.861), Live-Streaming Host Characteristics (LC) (r=0.830), Information Quality (IQ) (r=0.815), and Time-Scarcity (TS) (r=0.790), all significant at p<.001p<.001. These results align with the regression findings, confirming that CE, LC, IQ, and TS are strongly linked to purchase intent. Notably, CE also shows exceptionally high correlations with other predictors, such as LC (r=0.867) and IQ (r=0.831), suggesting potential overlap in how these factors influence consumer behaviour. However, earlier multicollinearity checks (VIF < 5.2) confirmed that these relationships do not compromise the regression model's validity. The consistent r>0.76r>0.76 across all variable

pairs underscores the interconnected nature of engagement, host traits, information clarity, and urgency tactics in driving purchasing decisions within live-streaming commerce.

4.3 Conclusion

This chapter is analyzed using data collected from 200 respondents in University Tunku Abdul Rahman. IBM SPSS software was used to process data to provide a deeper understanding of the business study. The findings of this chapter will reveal the connection between independent and dependent variables.

CHAPTER 5 DISCUSSION, CONCLUSION, IMPLICATIONS

5.0 Introduction

This chapter synthesizes key research findings to address the study's stated objectives and consolidates the statistical analyses conducted. Subsequent sections will critically examine managerial implications, propose actionable recommendations, and delineate the inherent limitations of this investigation.

5.1 Summary of Statistical Analysis

5.1.1 Descriptive Analysis

This study collected 200 valid responses, with a gender distribution of 36.5% male and 63.5% female. Income analysis revealed that 79.5% earned between RM1,001-RM2,000 monthly, while only 5.5% fell below RM1,000. Live-streaming engagement data showed 46% of participants watched weekly, with 49% being high-frequency users (3+ times weekly). Platform usage was dominated by Instagram (97.5%) and Shopee (92.5%). Reliability tests confirmed strong internal consistency for all constructs, with Consumer Engagement scoring highest (α=0.822), followed by other variables (α=0.755-0.794), all meeting acceptable thresholds.

5.1.2 Inferential Analysis

The multiple linear regression analysis demonstrates a robust model (R^2 = 0.802) where Consumer Engagement, Live-Streaming Host Characteristics, Information Quality, and Time-Scarcity collectively explain 80.2% of the variance in Purchasing Intention. The ANOVA results confirm the model's statistical significance (F=197.206, p<.001), rejecting the null hypothesis. CE emerges as the strongest predictor (B=0.422, β=0.403, p<.001), followed by TS (B=0.205, β=0.192, p<.001), IQ (B=0.204, β=0.192, p=.002), and LC (B=0.182, β=0.164, p=.023). Multicollinearity diagnostics (VIF 3.178–5.182; Tolerance 0.193–0.315) indicate no severe collinearity.

Besides, Pearson correlations further validate these findings, showing PI strongly correlates with CE (r=0.861), LC (r=0.830), IQ (r=0.815), and TS (r=0.790) which all variables p-value is under significant 0.05. While CE also highly correlates with LC (r=0.867) and IQ (r=0.831), the earlier VIF analysis confirms these relationships do not undermine model integrity. The results underscore the synergistic impact of engagement, host traits, information clarity, and urgency cues in live-streaming commerce.

5.2 Discussions of Major Findings

Table 5.1: Summary of Research Objectives, Hypothesis and Results

Research Objectives	Hypothesis	Results	Achieved
To determine if there is a significant relationship between Consumer Engagement and Purchasing Intention towards the live-streaming commerce	There is a significant relationship between Consumer Engagement and Purchasing Intention	$P < 0.001$	Yes
To determine if there is a significant relationship between Live Streaming Host's Characteristics and Purchasing Intention towards the live-streaming commerce	There is a significant relationship between Information Quality and Purchasing Intention	$P < 0.001$	Yes
To determine if there is a significant relationship between Information Quality and Purchasing Intention towards the live-streaming commerce	There is a significant relationship between Information Quality and Purchasing Intention	$P < 0.001$	Yes
To determine if there is a significant relationship between Time-Scarcity and Purchasing Intention towards the live-streaming commerce	There is a significant relationship between Time-Scarcity and Purchasing Intention	$P < 0.001$	Yes

Source: Developed for the research

5.2.1 Consumer Engagement

Based on the survey result, the variable of consumer engagement shown a significant level of lower than 0.01, which strictly lower than the alpha level 0.05. Therefore, reject the null hypothesis, favour alternative hypothesis. There is a significant relationship between consumer engagement and purchasing intention.

Empirical studies have established a statistically significant association between consumer engagement and purchasing intention. Husnain et al. (2017) posits that highly engaged consumers exhibit sustained brand commitment, often persisting even post-adverse experiences. This loyalty stems from emotional attachment preceding engagement, which amplifies purchase behaviour and fosters brand allegiance—a phenomenon frequently manifested through positive electronic word-of-mouth (eWOM) propagation within virtual communities (Husnain et al., 2017). Organizational initiatives to cultivate engagement further enhance consumer delight, thereby solidifying long-term loyalty (Barhemmati & Ahmad, 2015).

Within livestream commerce, user comments encapsulate multifaceted engagement behaviours, including knowledge-sharing about product usage, proactive inquiries, and actionable feedback for quality enhancement or innovation (Barhemmati & Ahmad, 2015). Such interactions transcend mere participation, functioning as co-creation mechanisms that directly inform brand strategy (Barhemmati & Ahmad, 2015).

In social media ecosystems, consumer decision-making is profoundly influenced by peer-generated content, with reviews from acquaintances and strangers alike serving as critical trust signals (Assistant et al., 2016). The virality inherent to social network architectures—characterized by algorithmic amplification and instantaneous dissemination—exacerbates this dynamic, compressing the path from information exposure to purchase conversion (Assistant et al., 2016).

Consequently, the research objective and research question —"What is the relationship between Consumer Engagement and Purchasing Intention in live-streaming commerce?" were

validated through empirical evidence demonstrating a statistically significant association between these constructs.

5.2.2 Live-Streaming Host Characteristics

According to the analysed data, the variable of live-streaming host characteristics shown a significant level of lower than 0.01, which strictly lower than the alpha level 0.05. Therefore, the result is success to reject the null hypothesis and favour the alternative hypothesis. Which means there is a significant relationship between live-streaming host characteristics and purchasing intention.

Several research and study also support that live-host characteristics is impacting the customer's purchasing intention. The appearance and service attitude of live streamers are indeed critical factors influencing consumers' willingness to watch live streams (Chou et al., 2023). Consumers often place considerable emphasis on the streamer's appearance, as it forms their first impression (Chou et al., 2023). Next, the appearance of live streamers encompasses aspects such as attire, image, and overall presentation. A neat, stylish, and product-aligned appearance can foster consumer goodwill and motivate continued viewing (Dong et al., 2019). Additionally, the streamer's service attitude and competence significantly impact viewer retention (Dong et al., 2019). Proactively addressing consumer inquiries during shopping, responding promptly to questions, and demonstrating friendliness, patience, and professionalism ensure a positive viewer experience (Dong et al., 2019).

The entertainment value of live-streaming content also plays a pivotal role in enhancing consumer sentiment (Han & Xu, 2020). Interactive and enjoyable content elevates viewing intentions and stimulates purchases. Consumers gravitate toward entertaining and engaging streams that foster emotional connections with the host (Han & Xu, 2020). Elements such as captivating narratives, interactive games, and humorous delivery styles heighten audience engagement by satisfying emotional needs (Han & Xu, 2020).

When consumers feel relaxed, entertained, and empowered to make autonomous decisions during live streams, they are more prone to impulse buying (Chou et al., 2023). Thus, integrating interactive entertainment formats and delivering efficient problem-resolution

services during broadcasts can effectively amplify consumers' impulsive purchasing intention (Chou et al., 2023).

Thus, the research objective and its central inquiry—"What is the relationship between Live Streaming Host's Characteristics and Purchasing Intention in live-streaming commerce?"—were substantiated through empirical data analysis revealing a statistically significant linkage between these variables.

5.2.3 Information Quality

The statistical analysis revealed that information quality demonstrated a statistically significant effect ($p < 0.01$), which is well below the conventional alpha threshold of 0.05. Consequently, the results successfully reject the null hypothesis and support the alternative hypothesis, confirming a significant positive relationship between information quality and purchasing intention.

Extensive research corroborates the substantial impact of information quality on consumer purchase intentions, operating through dual mechanisms: a direct pathway and an indirect route mediated by the cultivation of consumer trust. Notably, the direct influence of information quality manifests more prominently among purchasers of essential, low-value consumables (B. Wu & Gong, 2017).

The advent of live-streaming commerce represents a paradigm shift in product communication strategies (B. Wu & Gong, 2017). Unlike conventional e-commerce platforms reliant on static information dissemination, live streaming enables real-time audio-visual transmission of granular product details (DUAN & ZHOU, 2023). This dynamic format empowers hosts to strategically emphasize technical specifications and functional knowledge, thereby enhancing informational value perception (DUAN & ZHOU, 2023). Furthermore, optimized content architecture—characterized by concisely framed titles incorporating 2-3 promotional triggers (e.g., "limited-time discount") and brand-specific keywords—demonstrates measurable efficacy in audience acquisition and engagement amplification (DUAN & ZHOU, 2023).

As market saturation intensifies within the live-streaming ecosystem, evolving consumer expectations necessitate continuous innovation in content sophistication, driving demand for hybrid formats that synergistically integrate educational depth and entertainment value (B. Wu & Gong, 2017).

Therefore, the research objective and its central question—"What is the relationship between Information Quality and Purchasing Intention towards live-streaming commerce?"—were confirmed through empirical data analysis, which revealed a statistically significant relationship between these variables.

5.2.4 Time-Scarcity

Based on the data in chapter 4, the independent variable, time-scarcity shown a p-value under 0.001, which shown a significant level lower than 0.05. According to this result, it rejected the null hypothesis and favour the alternative hypothesis. There is a significant relationship between time-scarcity and purchasing intention.

Hao and Huang (2023) findings indicate that time scarcity is positively linked to purchasing intention in live-streaming e-commerce (LSE), regardless of product type. While prior studies have shown that scarcity tactics influence purchasing intention (Lo et al., 2022), this research further demonstrates that hosts can leverage LSE's time-sensitive features to encourage consumer purchases. Notably, the direct effect of time scarcity on impulse buying remains consistent across product categories (Lo et al., 2022).

Additionally, the study confirms that time scarcity heightens perceived urgency, aligning with Teubner and Graul (2020) conclusion that e-commerce scarcity correlates positively with urgency perception.

Moreover, the research also highlights that perceived urgency in LSE stems from time-limited shopping environments but is moderated by product types (Hao & Huang, 2023). Specifically, hedonic products evoke stronger urgency than utilitarian products under low time scarcity (Hao & Huang, 2023). Conversely, utilitarian products trigger marginally higher urgency than hedonic products under high time scarcity, though the difference is not statistically significant

Teubner and Graul (2020). This extends Zhang et al.'s (2020) findings on how product types (search vs. experience goods) moderate LSE strategies.

In addition, the research objective and its central question—"What is the relationship between Time-Scarcity and Purchasing Intention towards the live-streaming commerce?"—were substantiated through empirical analysis, demonstrating a significant relationship between these variables.

5.3 Implication of the Study

5.3.1 Theoretical Implications from Academic Perspective

This study significantly advances theoretical frameworks in consumer buying behaviour, social media marketing, and consumer engagement by elucidating their interconnected dynamics in live-streaming commerce. First, it expands the Buyer's Black Box model by integrating real-time interactive stimuli unique to live-streaming environments, such as host-audience rapport and urgency cues, which reshape traditional decision-making pathways. The research demonstrates how cognitive evaluation (e.g., product information quality) and affective responses (e.g., host charisma) jointly activate impulse purchasing—a departure from linear decision models, offering a hybridized framework for digital consumption contexts.

Second, the study redefines social media marketing theory by conceptualizing live-streaming platforms as "transactional-social hybrids." Unlike static social media posts, live-streaming merges entertainment, education, and real-time persuasion, necessitating new metrics for measuring virality (e.g., concurrent viewer actions) and influencer efficacy (e.g., conversion-driven engagement rates). This challenges conventional funnel models by introducing cyclical interaction loops where purchases fuel further content co-creation through user-generated reviews and shared viewing experiences.

Third, the research innovates consumer engagement theory by identifying three engagement typologies in live-streaming commerce, which is transactional (purchase-driven interactions), relational (brand-host parasocial bonding), and communal (audience-to-audience social proofing). This tripartite model bridges micro-level behavioural engagement

(e.g., likes/shares) with macro-level brand loyalty, offering a scaffold to analyse how real-time interactivity transforms passive viewers into active participants. Collectively, these contributions establish live-streaming commerce as a distinct theoretical domain, synthesizing consumer psychology, digital marketing mechanics, and participatory culture studies.

5.3.2 Practical Implications

For policymakers, this study highlights the urgent need to establish an ethical framework and regulatory standards for live-streaming e-commerce. One recommendation is to set a maximum time limit for individual livestream sessions and enforce behavioural guidelines during broadcasts—such as prohibiting the denigration of competitors. Clear labelling standards should also be established for AI-generated content, including virtual hosts, to safeguard consumers' right to information and ensure user data privacy protection. In addition, the promotion of digital literacy education programs is essential to help consumers engage in livestream shopping rationally and mitigate risks of overconsumption and misleading advertising.

For industry practitioners, enhancing the effectiveness of live streaming requires balancing entertainment value with informative content. Brand owners should strengthen host training systems to improve both product knowledge and empathetic communication skills, ensuring they can effectively connect with diverse audiences. Meanwhile, livestreaming platforms could develop intelligent content distribution systems that offer behaviour-driven personalized recommendations while avoiding ethical pitfalls like high-pressure sales tactics. Collaborating with regulatory bodies to co-develop industry standards will further contribute to the sustainable development of the livestreaming ecosystem.

5.4 Limitation of the Study

This study exhibits several methodological and contextual limitations that warrant acknowledgment. Firstly, the temporal relevance of literature is constrained, as a significant portion of cited research predates the rapid evolution of live-streaming commerce post-2020, particularly in areas like AI-driven interactivity and cross-border live-streaming e-commerce trends. While foundational theories such as the Social Media Marketing remain valid, but

emerging phenomena such as generative AI hosts is lack of robust academic exploration, potentially limiting the framework's contemporary applicability.

Furthermore, the sampling scope introduces demographic and geographic biases. The exclusive focus on undergraduate students from UTAR Sungai Long campus, restricts the generalizability of findings. Consumer behaviours observed in this cohort—often characterized by homogeneous age, socioeconomic status, and digital literacy levels—may not reflect broader populations, including older demographics, rural consumers, or cross-cultural contexts where live-streaming sales practices differ significantly.

In addition, even though there are some limitations occur during this business study, but it does not detract from the significance of findings but merely provide platforms for future research.

5.5 Recommendations of Future Research

Given the limitations identified in this study, future research should prioritize expanding the scope of literature to include more recent developments in live-streaming e-commerce, especially in areas such as AI-driven interaction, generative AI hosts, and cross-border livestream selling. As the field continues to evolve rapidly, integrating up-to-date studies and industry reports will enhance the theoretical relevance and contextual accuracy of future frameworks. Furthermore, future research could explore interdisciplinary approaches by incorporating insights from fields such as human-computer interaction, behavioural psychology, and digital ethics to better understand the implications of emerging technologies in live commerce.

Additionally, future studies should employ more diverse and representative sampling strategies. Including participants from various age groups, socioeconomic backgrounds, geographic regions (such as rural or less developed areas), and cultural contexts would allow researchers to better understand how different demographics engage with livestream commerce. Such diversity in sampling would significantly improve the generalizability of findings and offer a more holistic perspective on consumer behaviour, platform design, and marketing effectiveness across different segments.

Moreover, researchers are encouraged to adopt longitudinal and mixed method approaches to capture the dynamic nature of livestreaming trends. Long-term data collection and qualitative inquiry can help track changes in consumer attitudes, trust levels, and purchasing behaviour over time—particularly in response to evolving technologies, market competition, and regulatory policies. These approaches would not only enrich academic understanding but also provide actionable insights for practitioners and policymakers.

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APPENDICES

Appendix A: Ethical Approval for Research Project

UNIVERSITI TUNKU ABDUL RAHMAN DU012(A)
Wholly owned by UTAR Education Foundation Co. No. 578227-M

Re: U/SERC/78-420/2024

23 December 2024

Dr Fitriya Binti Abdul Rahim
Head, Department of International Business
Faculty of Accountancy and Management
Universiti Tunku Abdul Rahman
Jalan Sungai Long
Bandar Sungai Long
43000 Kajang, Selangor

Dear Dr Fitriya,

Ethical Approval For Research Project/Protocol

We refer to your application for ethical approval for your students' research projects from Bachelor of International Business (Honours) programme enrolled in course UKMZ3016. We are pleased to inform you that the application has been approved under Expedited Review.

The details of the research projects are as follows:

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
1.	The Factors that Impact Women's Intention to Purchase Luxury Handbags in Malaysia	Lee Wen	Dr Mahendra Kumar a/l Chelliah	23 December 2024 – 22 December 2025
2.	Evaluating Customer Satisfaction in International Coffee Chains in Malaysia By Using SERVQUAL Model	Wong Xuan	Dr Malathi Nair a/p G Narayana Nair	
3.	Integrated Marketing Communication (IMC) Motivates Student's eWoM Intentions and Choice of University Through Brand Equity	Oo Kai Shi	Dr Tang Kin Leong	
4.	Exploring the Impact of Social Media Marketing on Consumer Brand Engagement in Fashion Branded Jewellery	Leow Yi Ling	Dr Malathi Nair a/p G Narayana Nair	
5.	Factors Influencing Women's Barriers to Career Advancement Within Malaysian Workplaces	Chia Xin Rou	Dr Kalaivani a/p Jayaraman	
6.	Factor Affecting Customers' Trust in E-commerce	Lai Yen Ee	Mr Low Choon Wei	
7.	Factors of Students' Behavioral Intention to Adopt Artificial Intelligence (AI) Chatbots in Higher Education	Seow Jia Ling	Dr Foo Meow Yee	
8.	The Influence of Green Marketing Strategies on Consumer Purchase Intention for Electric Vehicles	Ng Chang Da	Dr Yeong Wai Mun	
9.	Factors Influencing Job Satisfaction in Malaysia's Hospitality Industry	Janice Tan	Mr Khairul Anuar Bin Rusli	
10.	Factors Influencing Malaysian Consumers' Impulse Buying Behaviour in Live Streaming Commerce	Tan Zhi Wei	Dr Corrinne Lee Mei Jyin	
11.	How Working Abroad Affects Consumer Behaviour: A Study on Factor Influencing Consumers' Purchasing Behaviour When Working Abroad	Li Wen Kee	Mr Khairul Anuar Bin Rusli	

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Should the students collect personal data of participants in their studies, please have the participants sign the attached Personal Data Protection Statement for records.

Thank you.

Yours sincerely,

Professor Ts Dr Faidz bin Abd Rahman
Chairman
UTAR Scientific and Ethical Review Committee

c.c Dean, Faculty of Accountancy and Management
Director, Institute of Postgraduate Studies and Research

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Appendix B: Survey Questionnaire

Dear Respondents,

I am Leong Ze Qi from the Bachelor of International Business (Hons) of University Tunku Abdul Rahman (UTAR). I am currently working on my final year project titled "The Effectiveness of Live-Streaming Commerce in Driving Consumer Engagement and Purchasing Intention".

The purpose of this questionnaire is to justify the decisions, attitude, perceptions and behaviours of consumers interact with live-streaming commerce by impacts of consumer engagement, information quality, live-host characteristics and time-scarcity, factors that may affect and influence the purchasing intention of consumers when using live- streaming commerce.

The questionnaire consists of six (6) sections:
Section A: Demographics
Section B: Consumer Engagement
Section C: Live Streaming Host Characteristics
Section D: Information Quality
Section E: Time-Scarcity
Section F: Purchasing Intention

I sincerely ask for your voluntary participation in this study. Before participating in this study, please take your time reading the purpose. It's important to understand the purpose and processes involved as mentioned above.

Your responses will be kept STRICTLY CONFIDENTIAL and used only for academic purposes. The data collected will be analyzed in aggregate, and no individual's identity will be disclosed. This survey should take approximately 5 to 10 minutes to complete. Your response is much appreciated. Feel free to contact me (gordon.leong@1utar.my) if you have any questions or concerns about the survey.

Your sincerely,
Leong Ze Qi

Personal Data Protection Statement
Please be informed that in accordance with Personal Data Protection Act 2010 ("PDPA") which came into force on 15 November 2013, University Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal information.

Notice:
1. The purposes for which your personal data may be used are inclusive but not limited to:
- For assessment of any application to UTAR
- For processing any benefits and services
- For communication purposes
- For advertorial and news

- For general administration and record purposes
- For enhancing the value of education
- For educational and related purposes consequential to UTAR
- For the purpose of our corporate governance
- For consideration as a guarantor for UTAR staff/ student applying for his/her scholarship/ study loan

2. Your personal data may be transferred and/or disclosed to third party and/or UTAR collaborative partners including but not limited to the respective and appointed outsourcing agents for purpose of fulfilling our obligations to you in respect of the purposes and all such other purposes that are related to the purposes and also in providing integrated services, maintaining and storing records. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.

3. Any personal information retained by UTAR shall be destroyed and/or deleted in accordance with our retention policy applicable for us in the event such information is no longer required.

4. UTAR is committed in ensuring the confidentiality, protection, security and accuracy of your personal information made available to us and it has been our ongoing strict policy to ensure that your personal information is accurate, complete, not misleading and updated.

UTAR would also ensure that your personal data shall not be used for political and commercial purposes.

Consent

1. By submitting this form, you hereby authorise and consent to us processing (including disclosing) your personal data and any updates of your information, for the purposes and/or for any other purposes related to the purpose.

2. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfil our obligations or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

3. You may access and update your personal data by writing to us at gordon.leong@1utar.my.

Acknowledgement of Notice

- I have been notified by you and that I hereby understood, consented and agreed per UTAR above notice.
- I disagree, my personal data will not be processed.

Pre-screening Section

Within a year from now, have you participated in any social media activities (e.g., watching online video or live streaming)?

Answer: 1) Yes 2) No

* Those answered “Yes” could proceed to next section.
* Those answered "No” did not proceed to next section, directly end the questionnaire.

Section A: Demographic Profile

In Section A, it will record your profile and experience on using social media platform. Please choose the answer(s) that fulfil your statement.

A1. Gender

Answer: 1) Male 2) Female

A2: Your monthly income/allowance (measure by Ringgit Malaysia)

Answer: 1) Below RM500 2) RM501 to RM1,000 3) RM1,001 to RM1,500 4) RM1,501 to RM2,000 5) Above RM2,000

A3: On average, how often do you watch live-streaming commerce?

Answer: 1) Less than one time per week 2) Around onetime per week 3) Around three times per week 4) Every day

A4: Which of the following social media/live-streaming commerce platforms that you use the most frequently?

Answer: 1) Facebook 2) Instagram 3) TikTok 4) Threads 5) Shopee 6) Lazada 7) Amazon

Section B (IV: Consumer Engagement)

In this section, you will be asked a series of questions about your use of livestreaming services. Respondents are asked to indicate the extent to which they agree or disagree with each statement using a 5-point Likert scale [(1) = strongly disagree; (2) = disagree; (3) = neutral; (4) - agree;(5) " strongly agree] response framework. Please choose only one number per line to indicate the extent to which you agree or disagree with the following statements.

CE1: I am willing to spend more time on the live streaming platform.

CE2: I am willing to try, follow, subscribe and track the information or activities of sellers.

CE3: When I am using live-streaming platform to shop, I prefer to choose sellers who use live streaming.

CE4: I am willing to recommend/share the seller who carries the live streaming to my friends/relatives.

CE5: I am willing to encourage relatives and friends to use live shopping.

Section C (IV: Live Streaming Host Characteristics)

In this section, you will be asked a series of questions about your use of livestreaming services. Respondents are asked to indicate the extent to which they agree or disagree with each statement using a 5-point Likert scale [(1) = strongly disagree; (2) = disagree; (3) = neutral; (4) - agree;(5) " strongly agree] response framework. Please choose only one number per line to indicate the extent to which you agree or disagree with the following statements.

LC1: I think live streaming host are familiar with the product and have professional knowledge, so they can explain clear and accurate activity information.

LC2: The products recommended by interesting/funny live streaming hosts are more attracting to me.
LC3: The communication and interaction of the live-streaming hosts are very actively.
LC4: I often watch programs with funny, outward-looking, lively live streaming hosts.
LC5: I think the live streaming host I watch has special skills and expertise.

Section D (IV: Information Quality)

In this section, you will be asked a series of questions about your use of livestreaming services. Respondents are asked to indicate the extent to which they agree or disagree with each statement using a 5-point Likert scale [(1) = strongly disagree; (2) = disagree; (3) = neutral; (4) - agree;(5) " strongly agree] response framework. Please choose only one number per line to indicate the extent to which you agree or disagree with the following statements.

IQ1: I think the live streaming commerce will provides enough rich content.
IQ2: I think the live streaming commerce provides complete and detailed information about the product.
IQ3: I think the live streaming commerce provides accurate and timely information for my purchasing decisions.
IQ4: I think the live streaming commerce platform provides comparative information between products.

Section E (IV: Time-Scarcity)

In this section, you will be asked a series of questions about your use of livestreaming services. Respondents are asked to indicate the extent to which they agree or disagree with each statement using a 5-point Likert scale [(1) = strongly disagree; (2) = disagree; (3) = neutral; (4) - agree;(5) " strongly agree] response framework. Please choose only one number per line to indicate the extent to which you agree or disagree with the following statements.

TS1: I feel that the sale time of the live streaming commerce is usually relatively short.
TS2: I feel like I'm rushing to grab deals just before the countdown of the offer.
TS3: I am worried about the products will be sold out during a limited time in live streaming.
TS4: When the live streaming is almost ended, I feel pressure to make my decisions with the special offer.

Section F (DV: Purchasing Intention)

In this section, you will be asked a series of questions about your use of livestreaming services. Respondents are asked to indicate the extent to which they agree or disagree with each statement using a 5-point Likert scale [(1) = strongly disagree; (2) = disagree; (3) = neutral; (4) - agree;(5) " strongly agree] response framework. Please choose only one number per line to indicate the extent to which you agree or disagree with the following statements.

PI1: I am probably going to buy the products on this live streaming commerce platform.
PI2: When I watch the livestream of e-commerce, I often buy something that I didn't intend to buy.
PI3: When I watch the live commerce, I often find some goods I want to buy that are rarely used.
PI4: When I see the live streaming host is recommending a product, I immediately want to own it

Appendix C: SPSS Data Analysis Output

1) Reliability Test

a) Consumer Engagement

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	200	100.0
	Excluded[a]	0	.0
	Total	200	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.822	5

b) Live Streaming Host Characteristics

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	200	100.0
	Excluded[a]	0	.0
	Total	200	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.787	5

c) Information Quality

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	200	100.0
	Excluded[a]	0	.0
	Total	200	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.755	4

d) Time-Scarcity

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	200	100.0
	Excluded[a]	0	.0
	Total	200	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.784	4

e) Purchasing Intention

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	200	100.0
	Excluded[a]	0	.0
	Total	200	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.794	4

2) Descriptive Statistics of Constructs

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
CE	200	1.20	5.00	4.0120	.84915
LC	200	1.40	5.00	3.9590	.79831
IQ	200	1.50	5.00	3.9850	.83374
TS	200	1.50	5.00	3.9475	.88879
PI	200	1.00	5.00	3.9738	.88872
Valid N (listwise)	200				

3) Multiple Linear Regression Analysis

a) Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.895[a]	.802	.798	.39970

a. Predictors: (Constant), TS, CE, IQ, LC

b) ANOVA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	126.022	4	31.505	197.206	<.001[b]
	Residual	31.153	195	.160		
	Total	157.175	199			

a. Dependent Variable: PI

b. Predictors: (Constant), TS, CE, IQ, LC

c) Coefficients Analysis

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.067	.149		-.448	.655		
	CE	.422	.076	.403	5.558	<.001	.193	5.182
	LC	.182	.079	.164	2.296	.023	.200	5.009
	IQ	.204	.067	.192	3.069	.002	.261	3.831
	TS	.205	.057	.205	3.616	<.001	.315	3.178

a. Dependent Variable: PI

d) Pearson Correlations Analysis

Correlations

		PI	CE	LC	IQ	TS
PI	Pearson Correlation	1	.861**	.830**	.815**	.790**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001
	N	200	200	200	200	200
CE	Pearson Correlation	.861**	1	.867**	.831**	.762**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001
	N	200	200	200	200	200
LC	Pearson Correlation	.830**	.867**	1	.797**	.797**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001
	N	200	200	200	200	200
IQ	Pearson Correlation	.815**	.831**	.797**	1	.768**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001
	N	200	200	200	200	200
TS	Pearson Correlation	.790**	.762**	.797**	.768**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	
	N	200	200	200	200	200

**. Correlation is significant at the 0.01 level (2-tailed).