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FACTORS THAT INFLUENCE GACHA GAME USERS' DECISION-MAKING IN USING GACHA GAMES

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ABSTRACT

The purpose of this study is to examine the factors that influence users' behavioral intention to use gacha games, employing the UTAUT2 framework. This study investigates the impact of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit on behavioral intention and use behavior of gacha games among users, with age serving as a moderating variable, considering users' familiarity with information technology nowadays.

Data were collected through an online questionnaire completed by 117 respondents aged 15 years and older, a demographic known for its familiarity with information technology and gaming. The questionnaire assessed respondents' perceptions of constructs derived from the UTAUT2 model. The analysis utilized SEM for testing the hypothesized relationships and determine the significance of each factor on behavioral intention and use behavior.

The results reveal that performance expectancy, hedonic motivation, and habit significantly impact behavioral intention. Conversely, effort expectancy, social influence, and price value have an insignificant impact. Additionally, behavioral intention is shown to have a significant impact on actual use behavior, underscoring the crucial role of users' intentions in determining their future use of technology. These findings suggest that perceived usefulness, enjoyment, and habitual use are critical drivers for the adoption and continued engagement with gacha games among users. The implications of this research emphasize the importance for game developers and marketers to enhance the user experience by focusing on these key factors to increase user engagement and retention.

Keywords: behavioral intention, gacha games, information technology, use behavior, UTAUT2.

INTRODUCTION

Human behavior has increasingly integrated with technology, driven by advancements that serve various aspects of daily life, including entertainment. One notable entertainment option is playing video games, particularly the gacha games, which has gained significant popularity among users of smartphones and other mobile devices. The term "Gachapon", that is originated from Japan, in the gaming industry, refers to a mechanism where users obtain characters, items, or other goods randomly through a virtual lottery system. Gacha games typically feature characters or units with varying rarity levels determined by the player's luck during draws, often using in-game currency or special items. The appeal of obtaining rare and powerful items drives many players to engage deeply with these games (C. Chen & Fang, 2023; Sofyandi, 2018).

Gacha games combine the role-playing game (RPG) elements, collection mechanics, and strategic gameplay. Players are challenged to collect characters or build strong teams for in-game challenges. Some gacha games offer intricate stories, while others focus on player-versus-player (PVP) battles. The business model of gacha games frequently relies on microtransactions, where players purchase in-game currency or special items to enhance their chances of acquiring desired characters or items. This model, while profitable, has raised concerns about addiction, excessive spending, and the gambling-like aspects of virtual draws (Heidhues et al., n.d.; Huang, n.d.; Lacik et al., 2023).

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Gacha games have captivated a wide audience globally. In Japan, significant expenditure on virtual items for social games is common, with individuals spending a notable portion of their monthly income on these items (Sofyandi, 2018). Gacha games have also achieved substantial success in other regions. For instance, "Fate/Grand Order" and "Genshin Impact" have seen remarkable financial success and widespread popularity. Genshin Impact alone generated $140 million in China and $20 million in the United States in September 2020, highlighting the game's global appeal (Franedya, 2020). As of January 2024, Genshin Impact boasts 67 million monthly active users, underscoring the significant interest and engagement with gacha games worldwide (Suhartanto, 2024).

The rapid advancement of Information Technology (IT) has dramatically altered many aspects of daily life, including entertainment. Gacha games, leveraging IT, offer an innovative and engaging platform that has garnered immense popularity. Understanding the acceptance of technology, especially in entertainment, is crucial for identifying the factors that motivate individuals to engage with new technologies. This study seeks to explore the technology acceptance in IT-based entertainment in a broader context, specifically focusing on gacha games.

A variety of factors might influence a person's intention to engage in a behavior, making it a pertinent area of research, especially in regions like Indonesia where engagement with gacha games is high. For example, a study by Kesuma & Princes (2024) found that a significant percentage of both males and females in metropolitan areas use mobile games for entertainment, with many willing to purchase items or characters to enhance their gameplay. Another study by Nelly & Prasetiyo (2023) indicated that smartphone development has facilitated high engagement with gacha games. Despite their popularity, academic research on gacha games remains limited, particularly in understanding the factors influencing their use and acceptance.

The intention of this study is to bridge the research gap by evaluating the behavioral intentions and use behavior of gacha game users by using the UTAUT2 model. Venkatesh et al. (2003) developed the UTAUT framework, which describes the determinants of technology use intentions. It has been expanded into UTAUT2, which includes the factors, such as that of effort expectancy, performance expectancy, facilitating conditions, social influence, hedonic motivation, price value, and habit (Correa et al., 2019; Tamilmani et al., 2021).

The intention of this study is to discover how these factors influence gacha game users' behavioral intentions and usage, with the goal of offering insights that will help developers, marketers, and policymakers together. This study seeks to provide an in-depth knowledge regarding the elements that drives the engagement with gacha games by analyzing both behavioral intentions and actual use behavior. By utilizing the UTAUT2 model, this study intends to participate in the academic understanding of technology acceptance in the context of IT-based entertainment, with particular emphasis on the gacha game genre.

CONCEPTUAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

This section elucidates the conceptual foundation employed in this research, providing a framework that delineates the relationships among the key research variables. Furthermore, it outlines the development of hypotheses that guide the investigation into the factors influencing users' behavioral intention and use behavior of gacha games, leveraging the constructs of the UTAUT2.

Gacha Games

Online games, which are digital or electronic games played via the internet access, have transformed the gaming landscape by enabling players to connect and interact within virtual environments. These games encompass numerous genres, namely: role-playing games (RPGs), first-person shooters (FPS), strategy games, and simulation games (Hobbs & Kelly, 1992). The immense popularity of online games can be attributed to their ability to foster social interactions, competitive gameplay, and cooperative experiences.

One prominent example of online games that has garnered significant attention is gacha games. The gacha system, an in-game feature typically found in the purchase menu, allows transactions using virtual currency that players can acquire with real money. Originating and gaining popularity in Japan, the term "gacha" refers to a vending machine dispensing capsules containing random toys, where the outcome is based on luck. This concept has been adapted into online games, where players can obtain random characters or items by engaging with the gacha system. Players have two options: earn free attempts by playing the game to acquire in-game currencies or use real money for in-app purchases through various payment methods. Points accumulated in the game are stored electronically on each player's device and are deducted when used. Each virtual item in the gacha system has a percentage chance of being obtained, a process known as microtransactions (C. Chen & Fang, 2023).

The gacha system comprises two main types: the point accumulation gacha system and the non-accumulation point gacha system. In the point accumulation gacha system, players are rewarded with points even if they do not obtain the desired item. These points can later be exchanged for prizes available in the gift menu. Conversely, the non-accumulation point gacha system does not reward points with each purchase, relying solely on chance and speculation. This type of system closely resembles gambling, where users do not know when they will gain and may even incur losses.

Gacha games have become a significant component of the online gaming industry, offering a blend of excitement and unpredictability that attracts players from diverse age groups and backgrounds. Understanding the mechanics and implications of the gacha system is crucial for analyzing user behavior and developing strategies for responsible gaming practices.

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

The theoretical framework of this study is grounded in the UTAUT2, an extension of the original UTAUT model proposed by Venkatesh et al. (2003). The UTAUT model was redeveloped to consolidate and expand on eight prevalent theories of technology acceptance: Theory of Reasoned Action (TRA)**,** Technology Acceptance Model (TAM)**,** Motivational Model (MM)**,** Theory of Planned Behavior (TPB)**,** Decomposed Theory of Planned Behavior (DTPB)**,** PC Model of PC Utilization (MPCU)**,** Diffusion of Innovation Theory (DOI**)**, and Social Cognitive Theory (SCT).

The UTAUT model identified four important variables that influence users' intentions and behaviors in relation to technology adoption performance expectancy, effort expectancy, social influence, and facilitating conditions (Martin, 2022):

- Performance expectancy, or how much technology can boost job performance.
- Effort expectancy, or the simplicity of utilizing the technology.
- Social influence, or the perceived importance of others’ belief in using technology.
- Facilitating condition, or individual’s belief in the availability of organizational and technological infrastructure to facilitate technology usage.
- Hedonic motivation, or the enjoyment gained from employing technology.
- Price value, or how consumers assess the perceived benefits of technology against the cost.
- Habit, or the automatic behaviors that individuals develop via learning.

Venkatesh et al. then introduced UTAUT2 in 2012, extending the original model to give further knowledge of technology acceptance and utilization in consumer contexts. UTAUT2 includes three extended constructs, namely: hedonic motivation, price value, and habit, thereby providing a more comprehensive explanation for technology use among general consumers (Venkatesh et al., 2012).

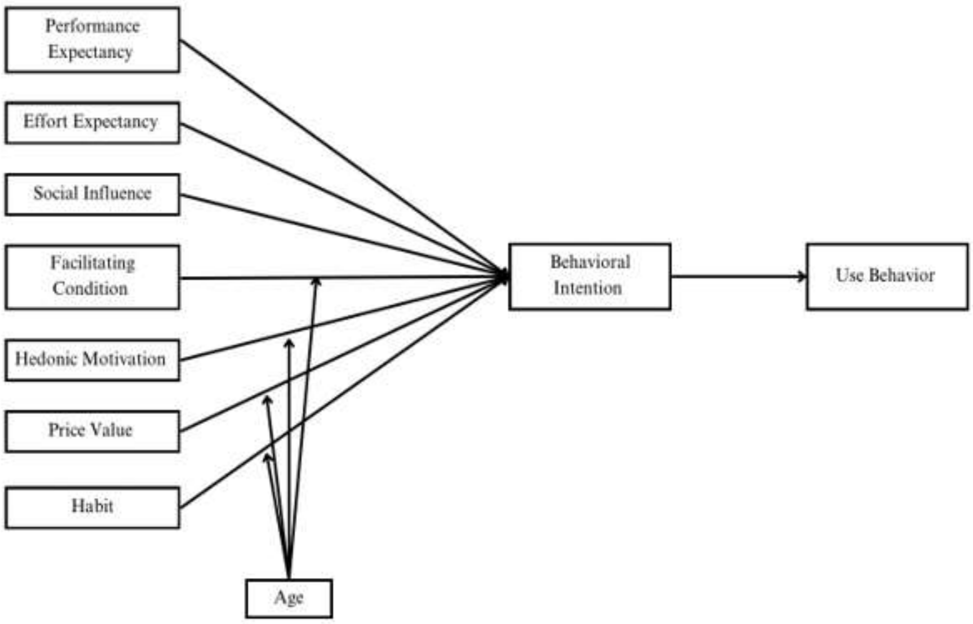
According to Correa et al. (2019), UTAUT2 attempts to provide a general explanation for why individuals use available information technology. It clearly defines the conditions for analyzing different types of technology users, such as mobile internet users, and extends the original UTAUT model, which was centred on technology use in organizations, to encompass everyday consumer technology acceptance and use (Tamilmani et al., 2021).

This theoretical framework serves as the foundation for exploring the aspects that influence users' behavioral intentions and usage behavior of gacha games, providing insights that can inform developers, marketers, and policymakers in enhancing user engagement and satisfaction.

Conceptual Framework

The conceptual framework illustrates the relationships among the research variables in a schematic form. This study employs dependent, independent, and moderating variables to evaluate the factors that influence users' intention and use of gacha games.

Figure 1.
Conceptual Framework



Hypothesis Development

Performance Expectancy Affects Users' Behavioral Intention to Use Gacha Games

Performance expectancy, or the notion that employing a system would boost one's performance. According to the UTAUT by Venkatesh et al. (2003), this is a vital component in determining an individual's intention to use technology, including gacha games. Studies by Nelly & Prasetiyo (2023) and Ericska et al. (2022) discovered that performance expectancy significantly impacts users' intention to use online games and freemium mobile games, respectively, as it improves usability, motivation, and performance. The following hypothesis are anticipated by this study:

H1: Performance expectancy exerts a significant impact on behavioral intention.

Effort Expectancy Affects Users' Behavioral Intention to Use Gacha Games

Effort expectancy, originated from the perceived ease of use in the Technology Acceptance Model (TAM), indicates the level of ease associated with utilizing a system (Venkatesh et al., 2003). Nelly & Prasetiyo (2023), Ericska et al. (2022), and Jang & Byon (2020) all demonstrated that effort expectancy significantly impacts the intention to use online, freemium mobile, and esports games, respectively. The following hypothesis is anticipated by this study:

H2: Effort expectancy exerts a significant impact on behavioral intention.

Social Influence Affects Users' Behavioral Intention to Use Gacha Games

Social influence pertains to how much an individual perceives that important others believe they should use a new system (Venkatesh et al., 2003). Studies by Correa et al. (2019) and Wibowo (2021) confirmed that social influence significantly impacts the intention to use online games, as modern online games often encourage social interaction and group play. The following hypothesis is anticipated by this study:

H3: Social influence exerts a significant impact on behavioral intention.

Facilitating Condition Affects Users' Behavioral Intention to Use Gacha Games

Facilitating condition is referring to the way which an individual thinks that organizational and technical infrastructure facilitates system usage (Venkatesh et al., 2003). Research by Chandra et al. (2022) highlighted that facilitating condition significantly impacts the intention to use online games, as support and resources enhance user engagement. The following hypothesis is anticipated by this study:

H4: Facilitating condition exerts a significant impact on behavioral intention.

Hedonic Motivation Affects Users' Behavioral Intention to Use Gacha Games

Hedonic motivation, the desire for fun and excitement, significantly influences the intention to use online and gacha games (Nelly & Prasetiyo, 2023; Correa et al., 2019; Kesuma & Princes, 2024). In gacha games, the thrill of obtaining rare items is a primary driver of user engagement. The following hypothesis is anticipated by this study:

H5: Hedonic motivation exerts a significant impact on behavioral intention.

Price Value Affects Users' Behavioral Intention to Use Gacha Games

Price value, which balances the benefits and the cost, is a key determinant in the technology usage (Venkatesh et al., 2012). Studies by Chaveesuk et al. (2021) and Jang & Byon (2020) found that price value significantly impacts the intention to use technology, including esports games. The following hypothesis is anticipated by this study:

H6: Price value exerts a significant impact on behavioral intention.

Habit Affects Users' Behavioral Intention to Use Gacha Games

Habit is the measure of how behavior is performed unconsciously through learned experience (Venkatesh et al., 2012). Research by Correa et al. (2019), Chandra et al. (2022), and Kesuma & Princes (2024) showed that habit significantly influences the intention to use online and gacha games. The following hypothesis is anticipated by this study:

H7: Habit exerts a significant impact on behavioral intention.

Behavioral Intention Affects Users' Use Behavior to Use Gacha Games

Behavioral intention, according to UTAUT2 by Venkatesh et al. (2012), directly affects the use behavior of technology. This was supported by studies from Nelly & Prasetiyo (2023) and Wibowo (2021), which demonstrated a strong correlation between behavioral intention and online gaming behavior. The following hypothesis is anticipated by this study:

H8: Behavioral intention exerts a significant impact on use behavior.

The Moderation Effect of Age on Behavioral Intention to Use Gacha Games

Age moderates the relationship between various factors (facilitating conditions, social influence, hedonic value, price value, habit) and behavioral intention (Venkatesh et al., 2016). Chang et al. (2019) also discovered that age moderates the link between social influence, price value, and behavioral intention. The following hypothesis is anticipated by this study:

H9: The moderation effect of age exerts a significant impact on behavioral intention.

RESEARCH METHODS

This section outlines the research methods used in this study, involving the population and sample, the data collection method, and data analysis method. The study employs a quantitative technique to collect and analyze data using figures and statistics, aiming to identify measurable patterns and relationships between variables. The Likert Scale, a five-point rating system, is utilized to gauge respondents' perspectives on gacha games, specifically their pricing and gain-loss experiences. The research targets gacha game users in Indonesia, including communities from popular games like "Genshin Impact Indonesia", "Honkai: Star Rail Indonesia", and "Wuthering Waves Indonesia (WWI)" on platforms such as Discord and Twitter. Following the guidelines from Hair et al. (2021), the sample size for this study, with seven independent variables, should be between 105 and 140 respondents.

Sampling Method

This research employed a purposive judgment sampling method. Purposive judgment sampling involves selecting participants based on the researcher's assessment of who will be the most informative or representative (Sekaran & Bougie, 2016). The study targeted individuals actively engaged with gacha games, as they possess the relevant experiences and insights needed. While this method ensured the data collected was rich and relevant, it may reduce generalizability.

Data Collection Method

The questionnaire will be the primary data gathering method employed in this study. Questionnaire consists of a preformulated written collection of questions to which the respondents record their answers, which are primarily limited to options with clear definitions. Questionnaire is a prewritten series of questions which are often restricted to options with explicit definitions, and is typically used to collect a large amount of quantitative data, as they could be sent directly to the responders via mail, e-mail, or private messages (Sekaran & Bougie, 2016). Furthermore, researchers will use online questionnaires to assist in reaching the appropriate respondents across various regions in Indonesia.

Data Analysis Method

This study employs the Structural Equation Model (SEM) for data analysis. SEM, as described by Garson (2016), is a path model that allows for the analysis of causal relationships between variables. By using SEM, researchers can better understand the connections between dependent and independent variables (Hair et al., 2021).
The analysis consists of two measurement models: the outer and inner models.

- Outer Model:
    - Validity Testing: Involves assessing both convergent validity (AVE and loading factors) and discriminant validity (cross-loadings)
    - Reliability Testing: Includes Cronbach's alpha and composite reliability, which require values above 0.7 for acceptance.
- Inner Model:
    - R-Square: Measures the model's explanatory power, where 0.775 indicates strong, 0.5 indicates moderate, and 0.35 indicates weak.
    - Q-Square: Evaluates the model's predictive relevance, where 0.35 indicates strong, 0.15 indicates moderate, and 0.02 indicates weak.
    - Path Coefficient: Tests hypotheses using t-statistics, requiring a t-value of >1.96 for one-tailed tests at a 5% significance level.

RESEARCH RESULTS AND DISCUSSIONS

Data Collection Results

This research utilized primary data collected through a questionnaire distributed to gacha game user communities in Indonesia over a one-month period in May 2024. Among the 117 respondents, 30.8% (36 respondents) were aged 15-20 years, 57.3% (67 respondents) were aged 21-25 years, 10.3% (12 respondents) were aged 26-30 years, and 1.7% (2 respondents) were over

30 years old. The majority of respondents were between the age of 21-25 age group, while the smallest group was those over 30 years old. Table 1 provides a more in-depth analysis.

Table 1.
Age of Respondents

Age	Frequency	Percentage
15 – 20 Years Old	36	30.8
21 – 25 Years Old	67	57.3
26 – 30 Years Old	12	10.3
> 30 Years Old	2	1.7
Total	**117**	**100.0**

Outer Model Testing Results

Outer model testing is a process that evaluates the indicators of each variable's validity and reliability in this study. The results of validity and reliability testing in this study utilizing SmartPLS are as follows:

Convergent and Discriminant Validity Testing

The SEM-PLS model was validated using convergent and discriminant validity tests. The findings of convergent validity tests are evident in tables 2 and 3.

Table 2.
Outer (Factor) Loading Value

Behavioral Intention		Use Behavior		Performance Expectancy		Effort Expectancy		Social Influence		Facilitating Condition		Hedonic Motivation		Price Value		Habit	
BI1	0.912	UB1	0.844	PE1	0.773	EE1	0.887	SI1	0.819	FC1	0.750	HM1	0.952	PV1	0.718	H1	0.880
BI2	0.902	UB2	0.863	PE2	0.892	EE2	0.899	SI2	0.825	FC2	0.853	HM2	0.977	PV2	0.911	H2	0.875
BI3	0.930	UB3	0.769	PE3	0.878	EE3	0.864	SI3	0.877	FC3	0.858	HM3	0.951	PV3	0.948	H3	0.777
				PE4	0.743	EE4	0.709			FC4	0.825						

Table 3.
Average Variance Extracted (AVE) Value

Variable	Average Variance Extracted (AVE)

Behavioral Intention	0.836
Use Behavior	0.683
Performance Expectancy	0.679
Effort Expectancy	0.711
Social Influence	0.707
Facilitating Condition	0.676
Hedonic Motivation	0.921
Price Value	0.748
Habit	0.715

Convergent validity testing is executed by measuring the loading factor and average variance extracted (AVE) value. To find out whether the data used has passed the convergent validity test, the loading factor values must exceed the critical value of 0.7, and the AVE values must be above the critical value of 0.5. Table 2 and 3 confirm that the outer loading and AVE values has been successfully passed the convergent validity. This means that the indicators are effectively measuring what they are intended to measure within the variable (Sekaran & Bougie, 2016).

The second test in the validity test is discriminant validity. It is a test to determine whether the concepts in the variables are different from each other (Hair et al., 2021). The outcomes from the discriminant validity testing are displayed in table 4.

Table 4.
Cross Loading Value

Behavioral Intention		Use Behavior		Performance Expectancy		Effort Expectancy		Social Influence		Facilitating Condition		Hedonic Motivation		Price Value		Habit	
BI1	0.912	UB1	0.844	PE1	0.773	EE1	0.887	SI1	0.819	FC1	0.750	HM1	0.952	PV1	0.718	H1	0.880
BI2	0.902	UB2	0.863	PE2	0.892	EE2	0.899	SI2	0.825	FC2	0.853	HM2	0.977	PV2	0.911	H2	0.875
BI3	0.930	UB3	0.769	PE3	0.878	EE3	0.864	SI3	0.877	FC3	0.858	HM3	0.951	PV3	0.948	H3	0.777
				PE4	0.743	EE4	0.709			FC4	0.825						

Cross loading value is the discriminant measurement in this research, in which each indicator in the variable must have a value above 0.7 to be declared valid (Hair et al., 2021). According to table 4, it can be claimed that the indicators employed in this study have a high and good discriminant validity value and are able to organize their respective variables.

Reliability Testing

Reliability testing in this research was performed to determine whether or not the indicators in each variable were good in order to form a latent variable. Reliability testing in this research employs two measurements: Cronbach's alpha and composite reliability. The findings of reliability testing are shown in table 5.

Table 5.
Results of Reliability Testing

Variable	Cronbach's Alpha	Composite Reliability
Behavioral Intention	0.902	0.939
Use Behavior	0.782	0.866
Performance Expectancy	0.842	0.894
Effort Expectancy	0.863	0.907
Social Influence	0.797	0.879
Facilitating Condition	0.841	0.893
Hedonic Motivation	0.957	0.972
Price Value	0.832	0.898
Habit	0.815	0.882

Reliability test measurements on SEM-PLS are implemented by examining the cronbach's alpha and composite reliability values, as they must be surpassing the value of 0.7 (Hair et al., 2021). Table 5 reveals that all variables in this study have high grade of reliability values and can be used for further testing. This is because the cronbach's alpha and composite reliability values for each variable surpass the critical value of 0.7.

Inner Model Testing Results

R-Square Test

The R-square test was employed in SEM-PLS research to examine the effect of the independent variable on the dependent variable in this study. The outcomes of the R-square test are presented in table 6.

Table 6.
R-Square Test Value

	R-Square	R-Square Adjusted
BI	0.482	0.422

UB	0.258	0.251

As illustrated in table 6, the R-Square value for behavioral intention variable is 0.482, while use behavior has a value of 0.258, demonstrating that 48.2% of the variance in behavioral intention and 25.8% variance in use behavior are explained by the independent variables in this study, with the remainder of variance is impacted by other factors. Three criteria are utilized to measure the strength of the structural model in SEM-PLS: the model can be said as strong if it has an R-square value of 0.775, moderate if it has an R-Square value of 0.5, and weak if it has an R-square value of 0.35 (Hair et al., 2021). In accordance with these provisions, both the behavioral intention and use behavior variables in this research have weak R-Square values.

Q-Square Test

In this research, the parameters in the structural model were evaluated, as well as the quality of the observed values, using the Q-square test. Table 7 reveals the findings of the Q-square test.

Table 7.
Q-Square Value

	Q^2
BI	0.360
UB	0.152

Table 7 illustrates a Q-square value of 0.360 for the behavioral intention variable and 0.152 for the use behavior variable. According to Hair et al. (2021), Q-square measurements can be classified according to their value, namely: if it is 0.35, it can be considered as strong, if it is 0.15, it can be considered as moderate, and if it is 0.02, it can be considered as weak. The results of the Q-square values show that the behavioral intention has a value of 0.360, indicating a strong Q-square value, while the use behavior has a value of 0.152, indicating a moderate Q-square value.

Path Coefficients

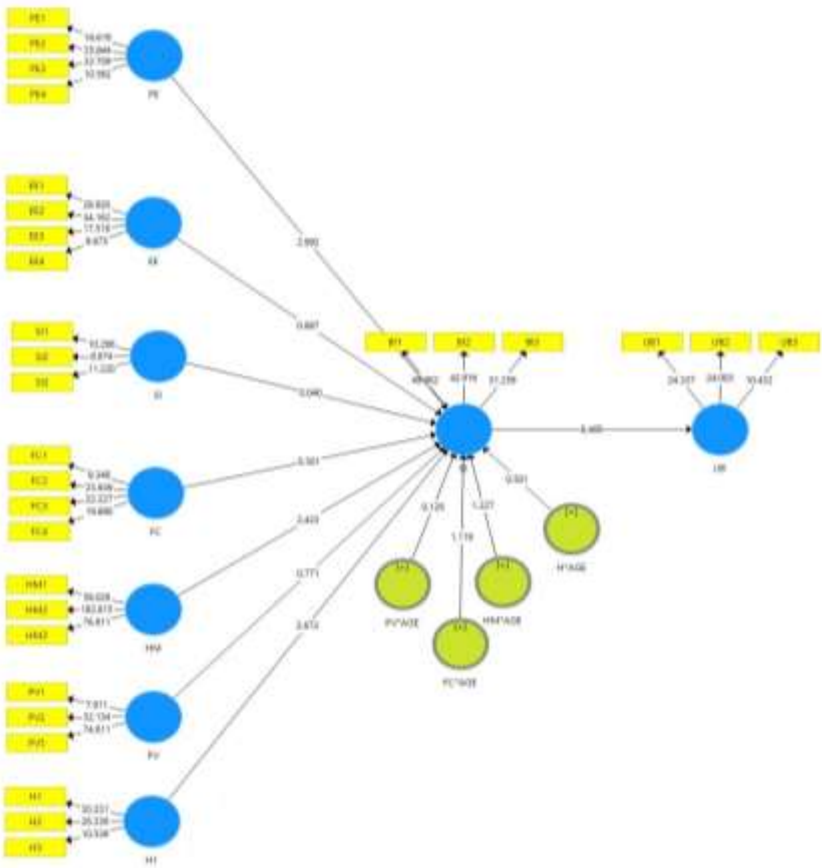
Hypothesis testing in this study is performed by using the path coefficient, which is carried out through the bootsrapping (t-statistics) test on SmartPLS. Table 8 reveals the results from the hypothesis testing.

Tabel 8.
Path Coefficient Test Results

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T-Statistics (|O/STDEV|)**	**P Values**	**Result**
PE -> BI	**0.253**	**0.257**	**0.085**	**2.992**	**0.003**	**Accepted**
EE -> BI	0.095	0.091	0.107	0.887	0.376	Denied
SI -> BI	0.003	0.009	0.081	0.040	0.968	Denied

FC -> BI	0.027	0.024	0.090	0.301	0.764	Denied
HM -> BI	**0.282**	**0.262**	**0.117**	**2.423**	**0.016**	**Accepted**
PV -> BI	0.069	0.073	0.089	0.771	0.441	Denied
H -> BI	**0.234**	**0.245**	**0.087**	**2.673**	**0.008**	**Accepted**
BI -> UB	**0.508**	**0.511**	**0.060**	**8.469**	**0.000**	**Accepted**
PV*AGE -> BI	0.013	0.002	0.105	0.128	0.899	Denied
HM*AGE -> BI	0.153	0.161	0.125	1.227	0.220	Denied
FC*AGE -> BI	-0.102	-0.104	0.091	1.119	0.264	Denied
H*AGE -> BI	-0.047	-0.050	0.095	0.501	0.617	Denied

Figure 2.
Path Coefficient Results



Hypothesis testing with SmartPLS is acceptable when the t-statistics value shows a value above 1.96 for the one-tailed model, and the p-value is below 0.05. As been shown on the table 8, there are several hypotheses that are accepted, but there are also several hypotheses that are denied. The explanation for each hypothesis is as follows:

H1 is accepted, showing that performance expectancy significantly impacts the behavioral intention to use gacha games (t-statistics = 2.992 > 1.96, p-value = 0.003 < 0.05). This finding aligns with Nelly & Prasetiyo (2023), who stated that performance expectancy significantly influences the intention to use online games. Users are motivated by the usefulness and benefits of the technology, increasing their interest in using it. When users find technology helpful in daily activities, their intention to use it rises.

H2 is denied, indicating that effort expectancy has no substantial effect on the behavioral intention to use gacha games (t-statistics = 0.887 < 1.96, p-value = 0.367 > 0.05). This finding aligns with Correa et al. (2019), who found that effort expectancy does not significantly influence the intention to use technology. Today's society, especially the younger generation (30.8% aged 15-20 and 57.3% aged 21-25), is already very familiar with online games and technology, making effort expectancy less impactful.

H3 is denied, indicating that social influence has no substantial effect on the behavioral intention to use gacha games (t-statistics = 0.040 < 1.96, p-value = 0.968 > 0.05). This finding aligns with Nelly & Prasetiyo (2023), who also found no substantial correlation between social influence and the intention to use technology. The intention to use IT is not greatly affected by the social circle of the users.

H4 is denied, indicating that facilitating conditions has no substantial effect on the behavioral intention to use gacha games (t-statistics = 0.301 < 1.96, p-value = 0.764 > 0.05). This finding aligns with Correa et al. (2019), who explained that facilitating conditions has no substantial effect on behavioral intention. Most people have easy access to technology, such as smartphones and the internet, especially younger respondents (30.8% aged 15-20 and 57.3% aged 21-25).

H5 is accepted, showing that hedonic motivation significantly influences the behavioral intention to use gacha games (t-statistics = 2.413 > 1.96, p-value = 0.016 < 0.05). This finding aligns with Nelly & Prasetiyo (2023), who found that hedonic motivation improves the intention to use technology. Kesuma & Princes (2024) explained that users are motivated by the joy and satisfaction of collecting rare items in gacha games.

H6 is denied, indicating that price value has no substantial effect on the behavioral intention to use gacha games (t-statistics = 0.771 < 1.96, p-value = 0.441 > 0.05). This finding aligns with Correa et al. (2019), who found that price value has no substantial effect on the intention to use technology. Free items reduce the importance of price value. Additionally, Wibowo (2021) stated that users are willing to spend money for an enjoyable experience, making price less critical.

H7 is accepted, showing that habit significantly influences the behavioral intention to use gacha games (t-statistics = 2.673 > 1.96, p-value = 0.008 < 0.05). This finding aligns with Correa et al. (2019), who discovered that habit strongly influences the intention to use technology. Users develop habits of using games regularly. Kesuma & Princes (2024) also noted that younger users (30.8% aged 15-20 and 57.3% aged 21-25) are more familiar with technology, reinforcing this habit.

H8 is accepted, showing that behavioral intention significantly influences the use behavior of gacha games (t-statistics = 8.649 > 1.96, p-value = 0.000 < 0.05). This finding aligns with Wibowo (2021), who found that behavioral intention significantly impacts use behavior. Stronger intentions lead to higher likelihood of technology use in the future.

H9 is denied, indicating that age has no significant influence on facilitating conditions, hedonic motivation, price value, and habit towards the behavioral intention to use gacha games (t-statistics = 0.128, 1.227, 1.119, and 0.501 < 1.96; p-values = 0.889, 0.220, 0.264, and 0.617 > 0.05). The demographic data supports these conclusions, showing that 30.8% of respondents are aged 15-20, and 57.3% are aged 21-25, indicating that the majority of respondents are tech-savvy younger individuals.

CONCLUSIONS AND LIMITATIONS

Conclusion

The following findings are derived from this research conducted on the gacha game user communities in Indonesia.

1. Performance expectancy has a significant correlation with behavioral intention to use gacha games.
2. Effort expectancy has an insignificant correlation with behavioral intention to use gacha games.
3. Social influence has an insignificant correlation with behavioral intention to use gacha games.
4. Facilitating condition has an insignificant correlation with behavioral intention to use gacha games.
5. Hedonic motivation has a significant correlation with behavioral intention to use gacha games.
6. Price value has an insignificant correlation with behavioral intention to use gacha games.
7. Habit has a significant correlation with behavioral intention to use gacha games.
8. Behavioral intention has a significant correlation with use behavior in gacha games.
9. Age, as the moderating effect, has an insignificant correlation with facilitating condition, hedonic motivation, price value, and habit on behavioral intention to use gacha games.

Limitations

Based on the researcher's direct experience during this research, several limitations were encountered. These should be considered for future research to enhance its quality and completeness:

1. The data collection was conducted in multiple platforms and communities, but the questionnaires were not classified and separated beforehand, leading to the possibility of getting duplicate responses from the same individuals.
2. The population includes a broad range of gacha game users, making the results less specific and not fully representative of the factors influencing users' interest in using gacha games.
3. During data collection, the responses may not accurately reflect the respondents' true opinions and experiences, as individual's perceptions and understandings vary.

Recommendations

Based on the research conducted on factors influencing interest in using gacha games, several suggestions can be provided:

1. Considering the high number of young people using gacha games, future research should also include how their traits affect their interest in these games. For instance, the current research indicates that hedonic motivation, where users use for fun and excitement, has a significant effect towards their behavioral intention to use gacha games and whether they want to keep using gacha games in the future. Therefore, future researchers could also study how much enjoyment users are having to identify more about what makes them interested in gacha games.
2. To facilitate the data collection process, future research should focus on a smaller geographic area where people have similar lifestyles and conditions. This approach would help researchers better understand their situations and make the research findings apply to more people.

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