

Determinants of Investment Intentions in Peer-to-Peer Lending Platforms: Evidence from Malaysia's Fintech Ecosystem

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Research Article

Keywords: Peer-to-Peer Lending, Investment Intention, Fintech Adoption, UTAUT, TIM, Perceived Trust, MSME

Posted Date: September 23rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11122388/v1>

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Additional Declarations: The authors declare no competing interests.

Abstract

Peer-to-Peer (P2P) lending platforms are a form of decentralized finance that use smart contracts to connect borrowers and lenders through online platforms. These platforms are expanding rapidly across Asia, including Malaysia, to address the financing needs of Micro, Small, and Medium-sized Enterprises (MSMEs). P2P LP also encourage financial inclusion by allowing individuals aged 18 and above to invest with a minimum amount of RM100. Despite increasing investor participation, the number of active investors remains insufficient compared to the funding demands of small businesses. Therefore, this study examines factors influencing individual investment intention in Malaysia's evolving fintech environment. Drawing on the UTAUT and the Technology Innovation Model (TIM), the study investigates the effects of social influence, effort expectancy, performance expectancy, perceived trust, and perceived time pressure on investment intention toward P2P platforms. Primary data were collected from 361 investors and potential investors in Malaysia and analyzed using SMARTPLS. The findings reveal that social influence and performance expectancy do not affect investment in P2P platforms. In contrast, effort expectancy, perceived trust, and perceived time pressure significantly influence individuals' intention to invest. In addition, the Importance Performance Matrix Analysis (IPMA) identifies individual perception and perceived trust as the most critical factors in strengthening investment intention and supporting the growth of the P2P lending market. These findings provide valuable acumens for platform operators, investors, borrowers, and policymakers in improving strategies, decision-making, transparency, and regulatory development.

1. Introduction

The P2P lending market has seen substantial expansion, growing from \$68 billion in 2021 to \$110.9 billion by the close of 2023, marking a compounded annual growth rate of 31%. Forecasts indicate this trend will persist, with the industry projected to reach \$1.168 trillion by the end of 2033 worldwide, adapting to the specific borrower demographics and preferences in each region (Precedence Research, 2024). This remarkable growth is driven by the increasing global digital user base and the accessibility of P2P lending platforms, which simplify the borrowing process by directly connecting borrowers with online lenders within a decentralized financial system. In recent years, P2P lending has emerged as a viable alternative to conventional banking services, particularly for Micro, Small, and Medium-Sized Enterprises (MSMEs) that often struggle to secure financing from traditional financial institutions. Consequently, a significant number of small businesses are increasingly relying on these innovative lending platforms to meet their financial needs, and the interesting fact is that funds are entirely supplied by investors and not the platforms.

While P2P lending platforms operate differently across countries, a common theme is their role in bridging financing gaps. For instance, in the United Kingdom, these platforms serve both business and individual borrowers, whereas in the United States, the primary focus is on individual lending. In contrast, China has positioned itself as a global leader in P2P lending volumes by emphasizing MSME financing, a model that Malaysia has also adopted, with its P2P lending platforms exclusively supporting MSMEs

(Kalabeke & Nguyen, 2023; Kizige et al., 2026). In Malaysia, P2P lending platforms play a crucial role in promoting financial inclusion and enhancing investment opportunities. MSMEs, which form the backbone of the Malaysian economy, contribute 37.4% to the GDP and generate over 80% of the country's employment (DOSM, 2023).

Despite their economic significance, MSMEs often face barriers in accessing financing from traditional banks due to stringent requirements and limited collateral. Malaysia's policy framework for MSMEs is encapsulated in the National Entrepreneurship Policy 2030 (Dasar Keusahawanan Nasional 2030, DKN 2030) aims to cultivate an inclusive and competitive entrepreneurial community which includes access to funding (World Bank Group, 2020). In alignment with this policy, the Malaysian government has implemented several initiatives in collaboration with P2P lending platforms to support MSME in fundraising through SARANA Financing Scheme, Catalysing MSME and MTC Access to Capital Markets. Hence, the growth of P2P market with total disbursements rising from RM32.6 million in 2017 to RM3.87 billion by mid-2023, benefiting 2,502 borrowers (SC, 2025).

Even with this expansion, a significant funding gap remains, as the demand for financing among MSMEs far exceeds the available investor resources. Currently, only a small fraction of the 1.2 million MSMEs in Malaysia benefit from these platforms, highlighting an unmet financial need. Current literature primarily focuses on the operational aspects and economic impact of P2P lending, yet there is limited understanding of the behavioral and technological factors influencing lending intentions to keep funds flowing. Secondly, due to concerns over insufficient consumer protection laws for retail investors, especially in relation to fraud and failed MSME projects, the need for better investor safeguards in P2P lending is evident. Although, the SC has implemented some measures, like capping investment amounts, many retail investors may lack the experience to navigate complex financial products (SC, 2021; Lee & Lim, 2020).

Addressing these gaps, this study applies the Unified Theory of Acceptance and Use of Technology (UTAUT) in conjunction with the Technology Innovation Model (TIM) to examine key factors that investors may consider when making decisions on P2P lending to help mitigate risks and ensure more informed choices. Findings from this study will inform strategies to improve investor participation, optimize lending processes, and strengthen regulatory frameworks, ultimately fostering a more inclusive and sustainable P2P lending ecosystem in Malaysia and supports global development of adaptive policies and innovative financial solutions.

The remainder of the article is organized as follows: Section 2 explores underlying theories and reviews related studies and formulates the research hypotheses. Section 3 outlines the research methodology employed in this study. Section 4 presents empirical results, discusses the implications, offers conclusions, and provides recommendations.

2. Theory and Literature Review

2.1 Underlying Theory

The chief of theoretical models for understanding technology adoption is the Technology Acceptance Model (TAM), proposed by Davis (1989). The model posits that two primary factors - Perceived Usefulness and Perceived Ease of Use influence technology adoption, these factors directly influence the behavioral intention to use technology, which subsequently predicts actual usage. TAM has been widely used in studies examining user acceptance of new technologies, including P2P lending platforms. However, it has been critiqued for its simplicity and lack of consideration for social and facilitating conditions, which are crucial in the context of financial technologies. A more comprehensive model designed to understand and predict technology adoption and usage behavior is the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003). The theory integrates elements from eight prominent technology acceptance models and posits that four core constructs influence behavioral intention and technology use which are Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions. These core constructs are moderated by variables such as gender, age, experience, and voluntariness of use. Despite its robustness, some researchers (Yuliani et al., 2024) have criticized UTAUT for its limited ability to predict individual behaviors in more complex and nuanced contexts, such as P2P LP. As a result, literature suggested extending UTAUT by incorporating additional constructs to enhance its predictive power (Chao, 2019). Therefore, this study proposes to integrate three additional constructs employed from the Technology Impact Model (TIM), introduced by Ozili (2024), specifically addressing the socio-economic implications of digital financial technologies.

TIM posits that the adoption of financial technologies like P2P lending is influenced by economic benefit Perception, technology Trust, and social cultural norms. In this case, Perceived Time Pressure. These constructs are considered essential in predicting the intention to invest in P2P LP. While UTAUT variables - Performance Expectancy, Effort Expectancy, and Social Influence address individual and social factors. Integrating both models aligns with theoretical triangulation, combining complementary perspectives to enhance predictive accuracy by capturing both user-centric and environmental dimensions, promoting a complete understanding of adoption behaviors (Venkatesh et al., 2016). This synergy supports more accurate and contextually relevant insights, particularly useful in technology-driven sectors where both user perception and situational factors shape adoption decisions. Based on these factors, the research framework is constructed as given in *Fig. 1*.

2.1 Usage Intention

"Intention" as an element in the UTAUT and TIM portrays user's intention to engage with or adopt a specific technology. It represents the level to which an individual has generated conscious plans to perform or use a technology (Venkatesh, 2022). This concept is crucial because the intention is often seen as the most immediate predictor of actual usage behavior. Investment intention means the inclination of an individual or entity to allocate funds or resources to various investment opportunities. This concept encompasses the decision-making process and the underlying motivations driving the

commitment of capital to specific investment products. According to Dammon, Spatt, and Zhang (2001), investment can be interpreted as the distribution of consumption over time, meaning the act of saving current economic resources for future consumption with the expectation of increased wealth. P2P LP investment intention is the use of internet platforms/smartphone applications to allocate resources to prospective borrowers to earn interest. Zahera and Bansal (2018) reviewed behavioral finance literature to understand the behavioral patterns of investors. They identified investors' perception, information asymmetry, risk aversion, and financial education influencing investors' intention and decision, and their behavioral biases include bullishness, nature effect, herding, loss aversion, rational accounting, representativeness, validation bias, and home bias, and self-attribution. Park and Oh (2022) identify EE, PE, SOI and FC as factors affecting individual investments intention. Therefore, it is imperative to measure P2P LP individual investment intentions.

2.2 Effort Expectancy, Performance Expectancy and Social Influence

Effort expectancy (EE) refers to the level of ease involved in the use of an information system (Venkatesh et al., 2021). Individuals are influenced by how user-friendly, intuitive, and accessible the investment platforms or applications are. If the process of investing in Fintech is perceived as straightforward and convenient, it can enhance investment intention. On the other hand, if it is perceived as complicated or requires significant effort to understand and use, it may deter potential investors (Fernando et al., 2021). Research indicates that EE, both directly and indirectly through perception as a mediator, significantly impacts individuals' intention to adopt fintech, including e-banking services. The convenience offered by e-banking systems influences users' behavioral intentions to use them. When customers perceive e-banking systems as easy to navigate and understand, they are more inclined to adopt and sustain their usage. User-friendly interfaces, streamlined processes, and intuitive design contribute to enhancing effort expectancy (Daka & Phiri, 2019; Mer & Viridi, 2021).

Performance expectancy (PE) is an individual's belief regarding the benefits they anticipate deriving from using a specific technology (Venkatesh et al., 2003). It plays a pivotal role in influencing technology usage by boosting users' motivation to engage with it. When individuals perceive a high level of PE linked to technology, it strengthens their inclination and drive to utilize it. Sukumaran et al., (2023) examined the behavioral inclination to use cryptocurrency in Malaysia. Their study, which included 290 respondents, suggests that PE, EE, and FC significantly influence the behavioral intention to use cryptocurrency. Other studies that adopt the UTAUT framework have also found its elements to be strong predictors of technology adoption intention in Malaysia. These include research on mobile payment usage intention, measuring the social behavioral aspects of using banknotes, the intention to use technology in Malaysian SMEs, and the intention to adopt cloud accounting among small businesses in Malaysia (Cheah et al., 2023; Solekah & Hilmawan, 2021). However, Nik Azman et al. (2024) findings suggest an insignificant effect of perceived usefulness on user intention directed at micro enterprises alternative revenue sources.

Social influence (SOI) refers to the extent to which people acknowledge the impact of significant others' beliefs on their decision to adopt a new information system (Venkatesh et al., 2003). In P2P LP, SI occurs when others' approval or disapproval influences an individual's decision to invest or refrain from investing. According to Venkatesh and Davis (2016), individuals may be motivated to adopt a behavior or technology if it is endorsed by one or more influential persons, even in the absence of personal expectations or perceived significant benefits from that behavior. Singh, Sahni, and Kovid (2020) investigated the drivers of fintech adoption among 439 internet users in Mumbai and Delhi. Their findings indicate that SOI negatively impacts the usage of fintech products. However, it positively influences perceived ease of use. Importantly, they found that SOI does not statistically influence behavioral intention and perceived usefulness in their study.

Furthermore, Lim et, al (2023) assessed consumer acceptance of on-demand digital platforms in Malaysia, they found that SOI, EE, PE and perceived risk significantly influence users' intention to use on-demand digital platforms. It implies that consumers are motivated to adopt technology to blend in with trends or connect with others. When consumers perceive that online platforms effectively meet their service or product needs on-demand and believe that the platforms enhance performance by saving time, providing convenience, and being effortless to use, they are more likely to repeat using these platforms. These findings are further validated in other studies (Yang & Lin, 2024; Bin & Wai Yie, 2025). Based on the sturdy foundation in contemporary studies above, the following hypotheses (H) are drawn.

H1: Effort Expectancy significantly influences perception towards investment intention in P2P LP

H2: Effort Expectancy significantly influences investment intention in P2P LP

H3: Performance Expectancy significantly influences perception towards investment intention in P2P LP

H4: Performance Expectancy significantly influences investment intention in P2P LP

H5: Social Influence significantly impacts perception towards investment intention in P2P LP

H6: Social Influence significantly impacts investment intention in P2P LP.

2.3 Perceived Trust (PT)

Yang and Lee (2016) explain trust as the inclination of lenders to believe the information provided on the platform about borrowers' businesses and its accuracy in meeting lenders' expectations. Lenders' trust in a P2P LP is built upon factors such as awareness, reputation, data security, confidentiality, usability, integrity, and the trustworthiness of the company or owner. Bao, Li, Shen, and Hou (2006) argue that trust is crucial in any business relationship, particularly in risky situations, with the Fintech industry being a prime example. Since online investment platforms are inherently riskier than conventional options, lenders need reasons or guarantees to boost their confidence to invest. Therefore, the more individuals find reasons to believe in the reliability of a Fintech service, the higher the chances of its adoption and usage. Thaker et al. (2019) investigation shows that the intention to lend money in a P2P LP is primarily

driven by trust in the borrower's information, including loan amount, payment periods, geographical location, stage of business, and industry. Similarly, Teo, Cheng & Chow, (2025) discovered that PT in e-service platforms significantly impacts the use of online platform services. Trusting the platforms reduces the perceived risk of anonymity, thereby increasing the likelihood of user benefits. Additionally, PT influence users' perceptions and their intention to continue using the platforms hence, the below hypotheses.

H7: Perceived Trust significantly influences perception towards investment intention on P2P LP

H8: Perceived Trust significantly influences investment intention on P2P LP

2.4 Perceived Time Pressure (PTP)

Phillips-Wren and Adya (2020) reviewed the literature on decision-making under stress and identified factors such as task complexity, uncertainty, information overload, and time pressure that cause stress and impair decision quality. They found that time pressure – a deadline imposed on completing a task leads individuals to make imprudent decisions due to insufficient time to consider all important data or aspects of the task, and potential outcomes. This increased stress can result in individuals making uninformed decisions, following others' decisions, or aligning with the general view. This situation can be problematic in P2P lending platforms which may cause herd mentality. Jarke-Neuert and Lohse (2022) argue that time pressure increases the prevalence of strategic ignorance, where individuals deliberately avoid certain information that could aid decision-making. They highlight that information avoidance often stems from a desire to avoid conflict. Consequently, when faced with time constraints, decision-makers may justify their actions by claiming insufficient information, which limits their ability to make informed decisions.

P2P lending platforms enforce a time limit to completing an investment and investors may not hold the platform accountable for not providing comprehensive information. This is often due to indemnity clauses and assertions from the platform that the information provided is sufficient for making profitable investment decisions. Hitherto, the hypotheses below.

H9: Perceived time pressure significantly influences perception towards investment intention on P2P LP

H10: Perceived time pressure significantly influences investment intention on P2P LP

2.5 Perception

Perception is referred to Individual interpretation of sensory information towards behavioral performance (Pickens, 2005). It is influenced by individual past experiences, expectations, Cultural background, and contexts. Perception is the behavioral intention which precedes actual performance, as individuals form intentions based on their subjective judgment of potential actions. Chuang, Liu, and Kao (2016) explored behavioral intention toward technology adoption in the Pakistan manufacturing industry. Their findings indicate that perception toward technology significantly influences behavioral intention to adopt technology. They also affirm that trust, perceived usefulness, and ease of use positively influence

individual attitudes toward technology adoption. According to Lai (2017), individual attitude mediates the intention to perform behaviors, as stated in the Theory of Planned Behavior and the original Technology Acceptance Model. Attitude mediates the connection between perceived usefulness, ease of use, and actual behavior. Ghazali and Yasuoka (2018) found that perceived benefits or usefulness which can be interpreted as PE positively influence user perception of fintech platforms among Malaysian MSMEs. The positive perception is driven by the high demand for funds and the benefits outweigh the costs. However, this may not be the same for investors, who face potential risks of losing their money invested.

In adopting technology such as a P2P lending platform, investors' perception – positively/negatively may play a crucial role in determining their investment intention and outcomes. From the above studies, it has been reaffirmed that the elements of UTAUT and TIM are viable predictors of whether individuals use technology. Hence, the following hypotheses are drawn.

H11: Individual perception significantly influences the investment intention in P2P LP

H12a: Perception mediates the relationship between Effort Expectancy and investment intention

H12b: Perception mediates the relationship between performance expectancy and investment intention

H12c: Perception mediates the relationship between social influence and investment intention

H12d: Perception mediates the relationship between Perceived Trust and investment intention

H12e: Individual Perception mediates the connection between Perceived time pressure and investment intention.

3. Methodology

The study employs a survey methodology, utilizing a purposive sampling technique to collect data from the target population. Survey methodology is widely regarded as an effective approach for obtaining quantitative data to capture insights into individuals' attitudes, behaviors, and perceptions from a large group (Groves et al., 2011). While the purposive sampling method was adopted to ensure that the study targets individuals who have specific characteristics needed to address the research question (Etikan et al., 2016), in this case, investors and potential investors in P2P LP in Malaysia. To collect data, we utilized a structured questionnaire and was divided into two distinct sections. The first section comprised 28 items designed to measure seven key constructs within the research model as shown in Fig. 1. These constructs included six independent variables—Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SOI), Perceived Trust (PT), Perceived Time Pressure (PTP), and Perception—and one dependent variable, Intention to Invest. Each construct was measured using four items. The items were developed based on established scales from previous studies, ensuring content validity and measurement accuracy (Venkatesh et al., 2003). A 5-point Likert scale was utilized to quantify the constructs, with responses ranging from "strongly disagree" (1) to "strongly agree" (5), which is consistent with best practices for measuring latent constructs in behavioral research (Hair et al.,

2019). The second section gathered demographic information on a nominal scale, capturing respondent characteristics such as age, gender, education level, race, and income level. Demographic data are essential for understanding the profile of respondents and for analyzing potential differences across groups (Hair et al., 2019).

Before conducting the actual test, we performed pre-tests to enhance the questionnaire's validity and reliability by evaluating the correctness and thoroughness of all measurement items (Hair et al., 2019). Reliability for each construct was assessed using Cronbach's alpha, with a benchmark of 0.7 (Hair et al., 2019). In the pre-test, we obtained 60 complete responses from investors and potential investors in P2P LP Malaysia. Cronbach's alpha scores ranged from 0.73 to 0.88, indicating that all variables surpassed the 0.7 threshold. Upon confirmation of the suitable level of reliability for all measurement items, the questionnaire was deemed reliable and applicable.

3.1 Participants

Data was obtained empirically using a cross-sectional survey. The questionnaire was distributed through the authors' networks via Google Form. This data collection was anonymous, ensuring that participants could not be identified. There were no name lists or contact details corresponding to the questionnaire respondents, eliminating any risk to the participants. All respondents were told about the research and assured them confidentiality of data would be maintained, and that their responses would be used solely for academic endeavors. It took respondents 12–15 minutes to complete the questionnaire. 372 responses were received, and after cleaning for suspicious responses, 361 were realized and used for analysis. This sample size was established according to the minimum required sample size ($n = 110$) for Structural Equation Models (SEM) of mediation with four indicators and a factor loading > 0.70 (Sim, Kim & Suh, 2022).

The demographic characteristics of the participants show that 40% of participants were between the ages 31 to 40 and 33.8% were 18 to 30 years. Approximately 53% of the participants were male and 43% female. Out of which, 58.2% were bachelor's degree holders and 33.5% were Postgraduate and professional qualifications. Also, 55.1% of the sample were Employed, and around 23.2% were students. Additionally, 45.4% of the respondents had a B40 income level, 40.2% were M40 and 14.4% were T20 income group.

4. Empirical Result

PLS regression is a commonly adopted SEM technique used to validate structured data (Ramayah et al., 2018) hence, this research employed PLS regression to implement bootstrapping for the research model, test and confirm the proposed model and the associations among the hypothesized constructs. A common-method bias test was conducted to ensure data quality, and Importance Performance Matrix Analysis (IPMA) was performed for managerial insights.

Before proceeding with testing the model, Common method bias (CMB) is checked, for the fact that a cross-sectional study such as this and the nature of questionnaire (5-point likert scale), a common-method variation poses a daunting challenge (Hair et al., 2017). Nonetheless, procedural remedies were incorporated during data collection, such as ensuring anonymity and emphasizing the importance of honest responses, we went further to create a new variable with random values as suggested by Kock (2020). PLS algorithm is executed containing the new random variable with the constructs, and the Variance Inflation Factors (VIFs) within the "inner model" are examined. VIFs higher than 3.3 indicate extreme collinearity, implying the presence of common method bias flaw. Upon examination we found out that VIFs for all constructs are below 3.3 hence there is no issue with common method bias contamination.

4.1 Measurement model Evaluation

Reliability, convergent and discriminant validity were evaluated to assess the measurement model. Internal reliability was measured using Cronbach's alpha and composite reliability values, while the average variance extracted (AVE) was employed to evaluate convergent and discriminant validity of the constructs, with a threshold set at 0.50. (Hair, Sarstedt, & Ringle, 2019). Table 1 presents the item loadings range, AVE, Cronbach's alpha, and composite reliability results. The items' outer loadings, which exceeded the recommended levels, ranged from 0.7 to 0.889 (Hair, Howard & Nitzl, 2020). And the AVE constructs surpass the 0.5 threshold, revealing that each construct describes at least 50% of the variation in its respective indicators on average. And Cronbach's alpha values for each construct start from 0.756 to 0.892. According to Hair, Sarstedt and Ringle (2019) composite reliability coefficients above 0.70 are appropriate, while values of 0.95 or higher indicate redundancy in measurement items. Composite reliability values for the various constructs in this study ranged from 0.845 to 0.925, suggesting that the indicators appropriately measure the constructs without redundancy.

Table 2 further outlines discriminant validity using the Heterotrait-Monotrait ratio (HTMT) which assesses the distinctness of constructs in a study. And the methods of determining discriminant validity under HTMT are the criterion and statistical approach. The criterion method uses a stringent threshold of 0.85 or 0.90 for the HTMT ratio; values lower than 0.90 indicate good discriminant validity (Teo, Luan & Sing, 2008; Schubert, Rademaker & Henseler, 2023), meaning that if HTMT values for all construct pairs are lower than 0.90, there is no concern regarding discriminant validity. The assessment results reveal all values < 90 percent confidence interval, affirming the presence of discriminant validity between the constructs.

Table 1
Convergent Validity, Internal Consistency and Reliability

Convergent Validity		Internal Consistency Reliability		
Construct /Indicator	Factor Loading	AVE	Cronbach's Alpha	Composite Reliability (rho_c)
Effort Expectancy (EE)		0.666	0.832	0.888
EE1	0.816			
EE2	0.7			
EE3	0.889			
EE4	0.848			
Performance Expectancy (PE)		0.673	0.841	0.892
PE1	0.803			
PE2	0.818			
PE3	0.841			
PE4	0.819			
Social Influence (SOI)		0.628	0.805	0.87
SOI1	0.774			
SOI2	0.852			
SOI3	0.833			
SOI4	0.703			
Perceived Trust (PT)		0.578	0.756	0.845
PT1	0.713			
PT2	0.728			
PT3	0.779			
PT4	0.817			
Perceived Time Pressure (PTP)		0.644	0.822	0.879
PTP1	0.801			
PTP2	0.822			
PTP3	0.79			
PTP4	0.797			

Convergent Validity		Internal Consistency Reliability		
Perception (PRTN)		0.743	0.884	0.92
PRTN1	0.85			
PRTN2	0.889			
PRTN3	0.824			
PRTN4	0.884			
Investment Intention (INT)		0.755	0.892	0.925
INT1	0.873			
INT2	0.882			
INT3	0.833			
INT4	0.887			

4.1 Model Assessment

To measure the whole effectiveness of the proposed model, the “goodness of fit” (GoF), “Standardized Root Mean Square Residual” (SRMR) was employed. This measures the average standardized difference between observed and predicted correlations, suitable for evaluating composite models fit. A lower SRMR value is indicative of a better fit which is suggested to be below 0.08 (Schubert, Rademaker & Henseler, 2023). Upon running the path Pls-algorithm, the estimated result of SRMR shows 0.076, indicating a good fit, hence, suggests that the model's predictions are very close to the actual data.

Path coefficient and t-statistics were employed to evaluate the relationships among the latent and endogenous variables. The coefficients are determined using the bootstrap resampling method with 10,000 iterations. The hypotheses regarding the direct relationships between EE, PE, SOI, PT, PTP, Perception, and Intention are illustrated in Table 3, and presented the structural model in *Fig. 2*.

The results, presented in Table 3. indicate that only five relationships exhibited t-values exceeding 1.645 in a two-tailed test, significance at the 0.05 and 0.01 level. Among these five relationships, EE and Perception ($\beta = 0.401$, $t = 8.587$, $p < 0.01$) PT and Perception ($\beta = 0.346$, $t = 7.004$, $p < 0.01$), PT and Intention ($\beta = 0.136$, $t = 2.054$, $p < 0.05$), PTP and perception ($\beta = 0.234$, $t = 4.817$, $p < 0.01$), Perception and Intention ($\beta = 0.696$, $t = 11.373$, $p < 0.01$). Therefore, H1, H7, H8, H9, and H11 are supported. This means that EE, PT and PTP positively influence individual perceptions towards P2P LP. Then PT and Perception positively influence intention to invest in P2P LP with an explanatory power $R^2 = 0.673$ and $R^2 = 0.644$ respectively.

Table 3
Results for Structural Model Hypotheses H1 to H11

Hypothesis	Relationship	Std Beta	Std Error	t-value	p-value	Decision	R2
H1	Effort Expect -> Perception	0.401	0.047	8.587**	0	Supported	0.673
H2	Effort Expect -> Intention	-0.025	0.05	0.504	0.615	Not Supported	
H3	Performance Expt -> Perception	0.006	0.031	0.208	0.835	Not Supported	
H4	Perform Expt -> Intention	-0.008	0.031	0.246	0.805	Not Supported	
H5	Social Influence -> Perception	0.032	0.031	1.018	0.309	Not Supported	
H6	Social Influence -> Intention	-0.059	0.037	1.628	0.104	Not Supported	
H7	Perceived Trust -> Perception	0.346	0.049	7.004**	0	Supported	
H8	Perceived Trust -> Intention	0.136	0.066	2.054*	0.04	Supported	
H9	Perceive time Pressure -> Perception	0.234	0.049	4.817**	0	Supported	
H10	Perceive time Pressure -> Intention	0.058	0.049	1.182	0.237	Not Supported	
H11	Perception -> Intention	0.696	0.061	11.373**	0	Supported	
**Significant at p -value < 0.01 *Significant at p -value < 0.05							

4.2 Mediation Effect

We employed Preacher and Hayes (2008) approach to mediation testing, in the SmartPLS bootstrapping method of the Bias-Corrected and Accelerated Bootstrap technique. To confirm the presence of mediation, the most appropriate method is to utilize the "bias corrected bootstrap confidence interval". When the confidence gap does not include zero, the path coefficient is considered statistically significant at the 95% confidence level (Hayes & Scharkow, 2013). The mediation results and the indirect effects at a 95 percent confidence interval bias corrected (CIBC) for the five identified indirect effects are as presented in Table 4. The result show that three out of the five connections are significant; EE-> Perception -> Intention ($\beta = 0.235$, t -value = 7.15, $p < 0.01$) and (CIBC = 0.17, 0.306), PT -> Perception -> Intention ($\beta = 0.258$, t -value = 5.441, $p < 0.01$) and (CIBC = 0.171, 0.354), Per. PTP -> Perception ->

Intention ($\beta = 0.167$, $t\text{-value} = 4.518$, $p < 0.01$) and (CIBC = 0.099, 0.246). This suggests that the mediation effects are statistically significant at the 0.05 and 0.01 significance level, with $t\text{-values}$ exceeding 1.96 in a two-tailed test, and the results are further corroborated by the CIBC test (Preacher and Hayes, 2008; Hayes & Scharkow, 2013). Thus, hypotheses H12a, H12d and H12e are supported. Partial mediation is determined by the latent variable's direct effect on the dependent variable (Ballen & Salehi, 2021), as in the case of PT and intention to invest whereas, EE and PTP have no direct effect on intention hence a full mediation is established by perception.

Table 4 Results for Structural Model Hypotheses H12a to H12e

Hypothesis	Relationship	Std Beta	Std Error	t-value	p-value	CIBC		Mediation
						LL	UL	
H12a	EE -> Perception-> Intention	0.235	0.033	7.15**	0.000	0.177	0.306	Full
H112b	PE-> Perception-> Intention	0.004	0.019	0.196	0.845	-0.034	0.04	No
H12c	SOI -> Perception-> Intention	0.021	0.02	1.032	0.302	-0.02	0.06	No
H12d	PT-> Perception-> Intention	0.258	0.048	5.441**	0	0.171	0.354	Partial
H12e	PTP-> Perception-> Intention	0.167	0.037	4.518**	0.000	0.099	0.246	Full

Note: * $p < 0.05$, ** $p < 0.01$ at two-tailed CIBC = Confidence Interval Bias Corrected, LL=Lower Level, UL=Upper Level)

4.3 Importance and Performance Matrix Analysis (IPMA)

IPMA expands on the knowledge gained from path coefficient assessments within the structural model. This approach integrates the actual performance of each preceding construct relative to the target endogenous construct (Hock, Ringle & Sarstedt, 2010). IPMA incorporates additional measures, such as the average index values of the constructs. Figure 3 graphically illustrates the IPMA results, encompassing both total effects and index values of the constructs. The IPMA analysis for investment intention shows that perception is highly important but low performance, in other words, perception is crucial for investment intention but underperforming. Hence, P2P LP are encouraged to improve this construct to significantly enhance lending intention. Secondly, PT is moderately important but high in performance hence, it is critical to achieving high investment intention on P2P LP through perceived trust. While PTP and effort expectancy are in the lower quadrants, PE And SI are on the negative side. Since they are not impactful to investment intention in this study, they may not be considered for improvements at this stage of the P2P lending market. Also, Table 5 shows the summary of the hypotheses test

Table 5
Summary of Hypotheses test results

Hypothesis	Std Beta	t-value	p-value	Decision
H1	0.401	8.587**	0.000	Supported
H2	-0.025	0.504	0.615	Not Supported
H3	0.006	0.208	0.835	Not Supported
H4	-0.008	0.246	0.805	Not Supported
H5	0.032	1.018	0.309	Not Supported
H6	-0.059	1.628	0.104	Not Supported
H7	0.346	7.004**	0.000	Supported
H8	0.136	2.054*	0.04	Supported
H9	0.234	4.817**	0.000	Supported
H10	0.058	1.182	0.237	Not Supported
H11	0.696	11.373**	0.000	Supported
H12a	0.235	7.15**	0.000	Supported
H12b	0.004	0.196	0.845	Not Supported
H12c	0.021	1.032	0.302	Not Supported
H12d	0.258	5.441**	0.000	Supported
H12e	0.167	4.518**	0.000	Supported

4.4 Discussion

The study identifies that effort expectancy, perceived trust, and perceived time pressure significantly influence investment intention in P2P lending. Effort expectancy reflects the ease of using online platforms, while perceived trust reduces perceived risk by fostering confidence in platform reliability. Perceived time pressure encourages faster decision-making, though it may compromise thorough analysis. Additionally, individual perception mediates the relationships between these determinants and investment intention. These findings are similar to previous studies (Fernando et al., 2021; Pratama, 2021; Speier-Pero, 2019). However, the study finds that performance expectancy and social influence do not significantly influence investment intentions, likely due to the novelty of P2P lending and limited social interaction regarding these platforms as highlighted in other studies (Nguyen et al., 2021; Teoh, Yew & Heang, 2020; Xie et al., 2021). The analysis also reveals that individual perception partially mediates the relationship between perceived trust and investment intention but does not mediate the association between PE and SOI. Despite this, analyzing indirect effects through 95% CIBC suggests potential implicit influences, indicating the complexity of factors impacting P2P lending intentions. The findings mentioned above have important policy implications, particularly for regulators, platform operators, and stakeholders in the P2P lending ecosystem. Given the complexity and novelty of the P2P lending environment, targeted policies are crucial to enhancing investor confidence and promoting sustainable growth. One of the most critical policy implications is the need for a robust regulatory framework that fosters trust while minimizing risks. The positive relationship between perceived trust and investment intention highlights the importance of regulations that ensure platform transparency, accountability, and security (Mohd et al., 2019; Pratama, 2021). Regulatory bodies, such as the Securities Commission Malaysia, should continue to enforce comprehensive disclosure requirements that mandate platforms to regularly publish audited financial reports, performance metrics, and default rates. This will increase transparency and help investors assess risks accurately, thereby enhancing their confidence and willingness to invest. Furthermore, policymakers should introduce standardized cybersecurity guidelines to mitigate data breaches and fraud, which can significantly erode trust (Nguyen et al., 2021).

This aligns with global practices observed in more mature markets like the UK, where Financial Conduct Authority (FCA) regulations ensure that platforms meet stringent operational and risk management standards (Allen et al., 2020).

Secondly, Low levels of social influence and awareness indicate the necessity for educational campaigns that familiarize potential investors with the workings and benefits of P2P lending (Teoh, Yew & Heang, 2020). Government agencies and financial institutions should collaborate to develop educational programs and workshops that explain the mechanics, risks, and rewards of P2P lending. Increasing financial literacy will boost investor confidence and empower them to make informed investment decisions, thereby enhancing market participation (Lai, 2017). Thirdly, perceived time pressure significantly influences investment intentions, but it can lead to suboptimal decision-making (Amabile et al., 2002; Teo et al., 2025). Policymakers need to create safeguards that prevent impulsive and poorly informed investments. Hence, introduce cool-off periods where investors can reconsider their investment decisions without financial penalties. Similar practices have been implemented in consumer protection laws to reduce the impact of hasty decisions (Speier-Pero, 2019). Reducing time pressure may help mitigate cognitive biases, allowing investors to make more rational and well-evaluated decisions. Moreso, given that effort expectancy plays a crucial role in adoption, platforms should be held accountable for providing user-friendly interfaces and clear, understandable information. Regulators should establish usability and accessibility standards for P2P lending platforms to ensure that even less tech-savvy users can navigate them efficiently. By making platforms more intuitive and easier to use, investors' effort expectancy will be positively influenced, thereby boosting adoption rates. Additionally, regulators could implement policies requiring independent third-party audits of platform algorithms and decision-support systems to ensure fairness and accuracy (Xie et al., 2021).

5. Conclusion

The findings indicate that effort expectancy, time pressure, and perceived trust are the key factors impacting investment perception and intention, while performance expectancy and social influence are not significant. The study emphasizes the strong influence of perception on investment intention in P2P lending. Thus, the research has effectively addressed the research objective by examining the determining factors of P2P lending platforms that encourage investment intention. Additionally, it has highlighted the mediating role played by individual perception. Since the research reveals that social influence and performance expectancy did not impact investors' perception and intention, we recommend that the platforms focus on enhancing investors' awareness of the benefits and mechanics of P2P lending through educational initiatives. As improved awareness could empower investors to confidently advocate for P2P lending among their peers, potentially increasing adoption rates in this financial sector. In summary, the analysis of hypothesized relationships within the research model and the subsequent presentation and discussion of outcomes have made substantial contributions to advancing the understanding of behavioral studies, specifically in the domain of Fintech adoption through P2P lending. The discoveries of this study are particularly noteworthy as they offer imperative acumens into the dynamics of Fintech adoption within the Malaysian domain, thereby enriching

understanding of Fintech adoption, financial inclusion, and overall financial well-being for investors and MSMEs.

5.1 Implications for Society, Regulators/Polycymakers and Global Sphere

The findings of this study hold significant implications for both theoretical advancement and practical application, especially in the context of financial inclusion, investment promotion, and the development of P2P lending platforms in Malaysia. Theoretically, the study successfully integrates concepts from TIM and the UTAUT offering a more comprehensive understanding and unique characteristics of P2P LP, and how these integrated constructs influence user adoption and behavior within the Fintech context. As a result, future researchers can utilize these constructs to conduct targeted measurements, whether within P2P lending platforms or other Fintech systems. On practical and societal impacts, the study highlights that while P2P lending platforms are perceived as convenient and user-friendly, factors like performance expectancy and social influence do not significantly impact investor perceptions and intentions. Platform operators can use these insights to better address investor concerns and optimize their strategies. Additionally, the Importance-Performance Map Analysis offers guidance on enhancing investor perceptions and public awareness, promoting greater trust in P2P lending as a viable investment option. Ultimately, the study paves the way for increased investment, leading to financial inclusion and economic

Regulators and policymakers can derive substantial benefits from the study's findings. Key factors influencing investment intentions in P2P lending platforms are outlined, offering insights for regulatory bodies, such as Securities Commissions, to enhance industry stability and integrity. One essential recommendation is the implementation of enhanced transparency and disclosure measures. By fostering greater trust among investors and platform operators, regulators can ensure a more secure and reliable P2P lending environment. The study supports policy formulation aimed at incentivizing investments in P2P lending while maintaining financial stability. This can include investment facilitation such as tax incentives or subsidies for investors in P2P lending platforms to encourage adoption. On a global scale, the study highlights the similarities of P2P lending operations across different countries. This comparability allows for cross-country analysis and benchmarking (Widianoro et al., 2024) enhancing the global understanding of P2P lending practices. The findings can guide international regulators and policymakers to adopt best practices from Malaysia's P2P lending model by identifying globally relevant factors to formulate adaptive policies to foster safe and sustainable P2P lending ecosystems.

5.2 Limitations and Future Research

While this study provides significant theoretical, practical and policy implications, some limitations necessitate further exploration through future research attempts. Firstly, P2P lending regulations differ significantly across countries. This variation can affect the consistency and comparability of the

findings, limiting the generalizability of the results on policies and regulations. Secondly, the study primarily examined individual investors, neglecting the role and influence of institutional investors in the P2P lending sector. Considering that institutional investors significantly contribute funding to P2P LP hence, future research could explore their perspectives and behaviors using qualitative methods. This approach would provide deeper insights into how institutional investors perceive and engage with P2P lending platforms, enhancing understanding of their impact on the industry. Furthermore, the study used a cross-sectional approach to capture investor behaviors and market dynamics at a single point in time within the P2P lending industry. However, P2P lending platforms are dynamic, influenced by investor preferences, market conditions, and regulatory changes. To comprehensively understand these dynamics ultimately, imminent studies may employ longitudinal methods, allowing for the tracking of trends in investor behaviors, market conditions, and platform performance across multiple time points.

Declarations

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors confirm that there are no financial, professional, or personal affiliations, beliefs, or interests that could be perceived as affecting the objectivity or integrity of the research.

Informed Consent

Informed consent was obtained from all participants, and they were provided with details about the study's nature and purpose, as well as their right to withdraw at any time without facing any consequences.

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Figures

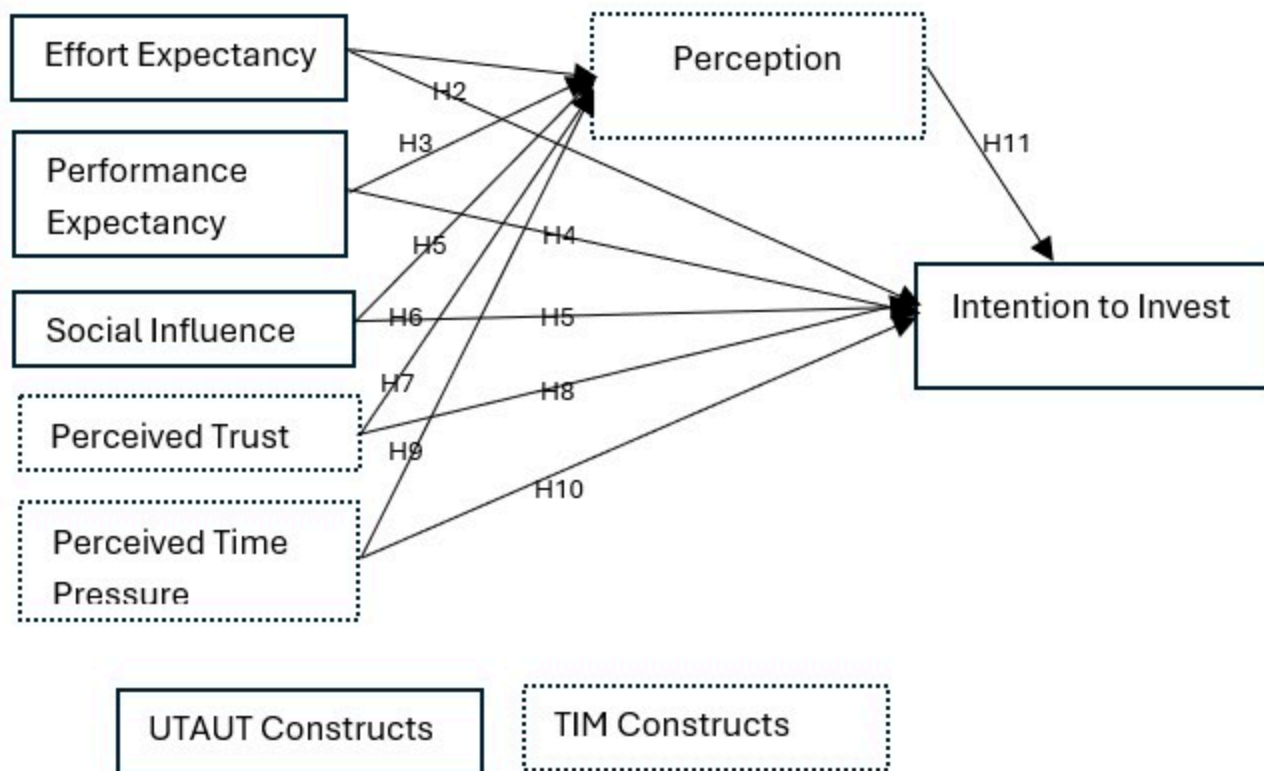


Figure 1

Research framework-combination of UTAUT and TIM

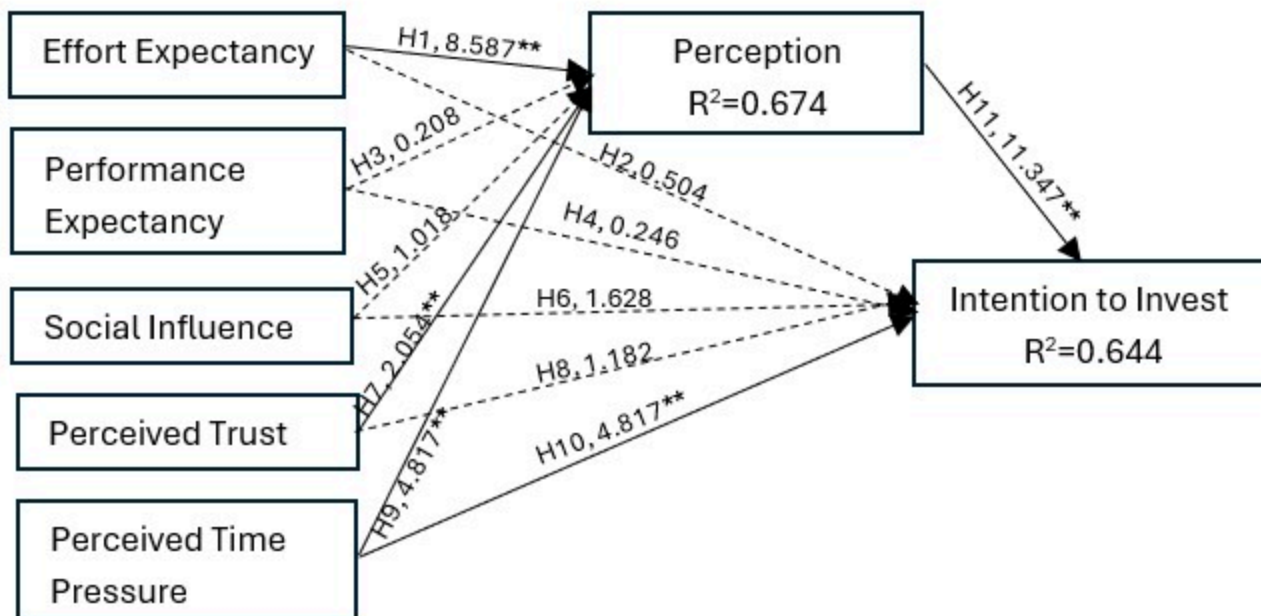


Figure 2

Structural Model

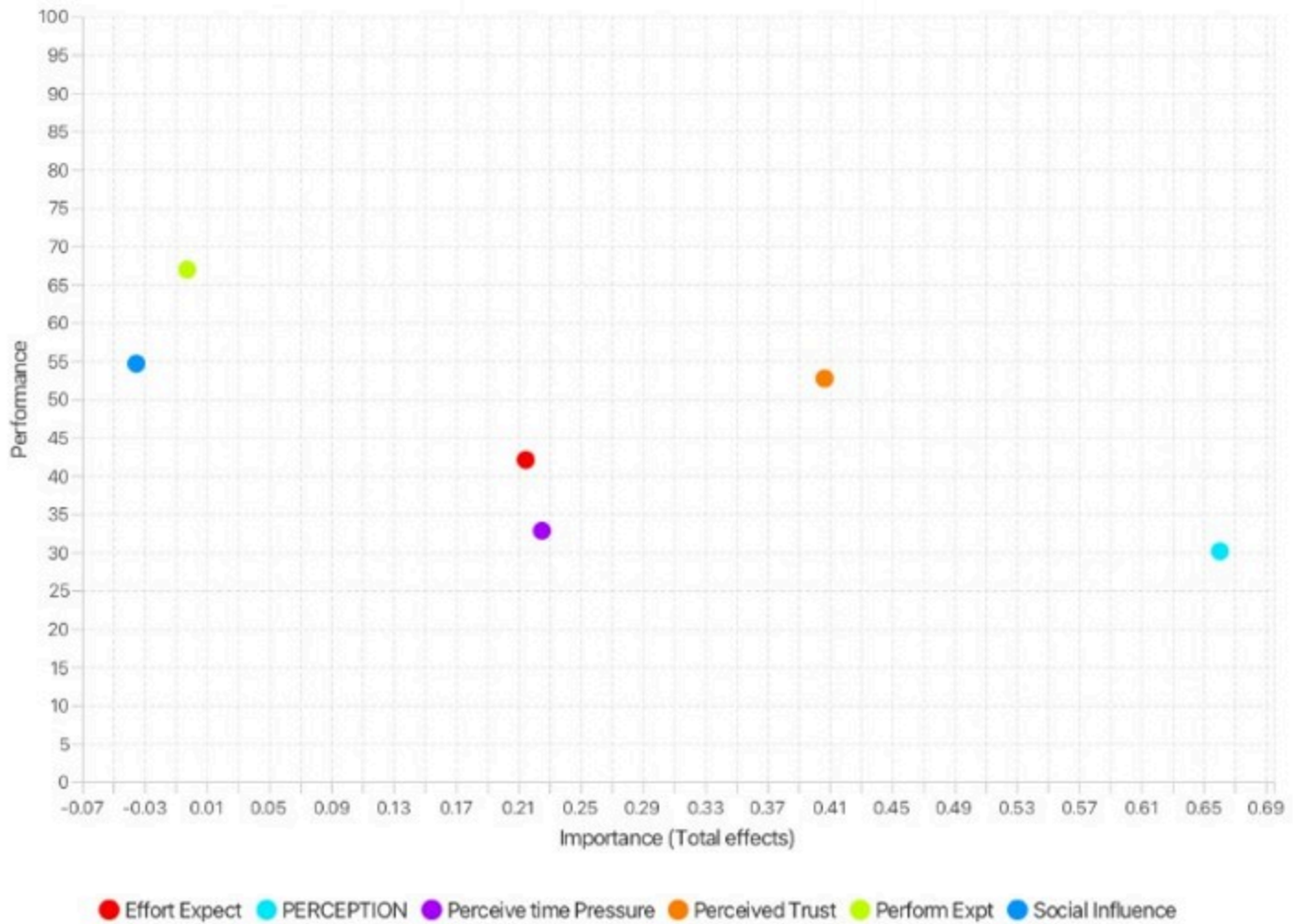


Figure 3: Importance and Performance Matrix Analysis

Figure 3

Importance and performance Matrix Analysis

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