# Integrating ChatGPT into Software Development: Valuating Acceptance and Utilisation Among Developers

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**Abstract**

This study examines software developers' acceptance and utilisation of ChatGPT, analysing its potential as an AI-driven programming assistant. Using the UTAUT2 framework and judgmental sampling, data was gathered from 335 developers over six weeks, starting in April 2024. The research assesses ChatGPT's impact on developers' workflows, focusing on determinants like Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, with additional consideration for Personal Innovativeness. Structural equation modelling reveals that Facilitating Conditions and Hedonic Motivation significantly influence developers' Behavioral Intention to use ChatGPT. Findings indicate developers view ChatGPT as a tool that enhances productivity and enjoyment in coding tasks, yet concerns remain about potential dependency and the AI's reliability. Moderating effects of Gender and Experience show nuanced influences, with experienced developers more inclined toward innovation. This research provides valuable insights for optimising ChatGPT integration, underscoring the importance of supportive resources and further refinement of AI tools in development contexts.

**Keywords:** Chat GPT, AI Acceptance, Developer Productivity, UTAUT2, Software Developers, PLS-SEM

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# Introduction

In the evolving world of technology, few innovations have gathered as much attention and debate as the dawn of artificial intelligence (AI). Among the various AI models, OpenAI's ChatGPT (Introducing ChatGPT, n.d.) stands out as a witness to the extraordinary advancements in (NLP)Natural Language Processing (Chowdhary, 2020). Promoted as an intelligent assistant, it can talk like a human in written conversation based on vast amounts of data, even conversations that challenge the boundaries between human and machine understanding. However, like many technological innovations before it, ChatGPT has its critics. Some view it as a tool that holds the promise of revolutionising industries, from customer service to education (Fraiwan & Khasawneh, 2023).

In contrast, others raise alarms about its potential misuse and the ethical importance surrounding its deployment. This paper seeks to explore the duality of ChatGPT: Is it a blessing that can push a software developer to new heights of knowledge and efficiency, or is it a curse that risks damaging the problem-solving skills of a software developer? (Strzelecki, 2023). Regarding software development, our tools and technologies can make a huge difference. Think of it as an intelligent assistant (Tian et al., 2023) that can help developers generate code, suggest fixes, or brainstorm ideas. For some, this sounds like a dream come true, a tool that can speed up projects, reduce errors, and make coding sessions less time-consuming (Akbar et al., 2023) (Jaber et al., 2023). However, only some people are on board. Some developers worry that relying on ChatGPT could mean fewer collaborations and brainstorming sessions between humans. They wonder if we could lose the unique creativity and problem-solving skills that only humans bring. With the recent introduction of the AI tool, we have limited insights into how developers perceive and adopt this new technology. We aim to conduct a study to understand the interest among developers in this tool, identify factors influencing its acceptance, and determine the depth of its adoption. To measure this technological acceptance, we plan to use elements from the famous "Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2003). Recent studies indicate that the UTAUT2 model assesses new technologies introduced into the professional technical areas, content generation (Agossah et al., 2023), digital assistant (Kononov, 2023), e-learning system (Kumbhar et al., 2021) and a tool for complex thinking(Romero-Rodríguez et al., 2023). Given this trend, we have opted to use this theoretical framework to explain developers' acceptance and application of ChatGPT.

This research is structured as follows: The introduction provides an overview of the development of ChatGPT and the ongoing discussions regarding its relevance in the software and tech community. In the methodology section, we dig into the UTAUT2 model and its application in understanding developers' acceptance and adoption of ChatGPT. We also present a customised measurement scale tailored specifically for ChatGPT's role in the development community. In the next section, we highlight the outcomes obtained from the structural equation modelling using the partial least squares approach, followed by an examination of the proposed theoretical framework. A broad discussion of our insights follows. In the conclusion of our study, we shed light on its unique contributions and significance to the developer community.

## Literature Review

### *Related Work*

Our research incorporates elements from the widely recognised "Unified Theory of Acceptance and Use of Technology" postulated by Venkatesh, Thong, and Xu (Strzelecki, 2023). This model outlines seven key determinants influencing technology adoption and intention: "Facilitating Conditions," "Habit," "Price Value," "Performance Expectancy," "Hedonic Motivation," "Effort Expectancy," and "Social Influence." Given ChatGPT's current free availability to all users, we intend to omit the "Price Value" determinant from our analysis. While a premium ChatGPT Plus version costs $20 monthly, offering enhanced features such as quicker response rates and priority access to new functionalities, the core ChatGPT service remains cost-free for all users. Extending our model, we are incorporating "Personal Innovativeness," a concept articulated by (Agrawal and Prasad, 1998) in 1998. For this research, we characterise "Personal Innovativeness" as an individual's tendency and capability to embrace and employ ChatGPT within their education framework. This characteristic represents a forward-thinking and occasionally driven perspective towards innovation, adopting transformation, and an enthusiasm for developing new knowledge.

Pair programming is a way for two developers to work on the same code. It is a good practice as it has its advantages and disadvantages. After introducing ChatGPT, a study explains whether we can consider it a programming partner (Imai, 2022)(Nguyen & Nadi, 2022). The famous Github copilot is an extension that provides various suggestions and can work like a virtual pair programming partner. The (Nguyen & Nadi, 2022) found that Copilot is a promising starting tool, producing accurate code in the 60% to 91% range, depending on the programming language used. The result of the promising advancement of these AI tools in content generation presents ethical dilemmas, including concerns about the quality, reliability, intellectual property rights, and accountability of the produced content. Concerning this, our approach leverages the UTAUT2 model (Venkatesh et al., 2003), and by employing this model, we aim to thoroughly assess if software developers not only accept ChatGPT as a mere informational tool but also perceive it as a programming partner.

In another study of ChatGPT in Software Development (Sudhir Bale et al., n.d.), findings showed ChatGPT could address 77.5% of the questions, providing accurate or partial answers for 55.6% and accurate or partial explanations for 53.0% of them. Using ChatGPT in a general query context resulted in slightly better outcomes (Jalil et al., 2023). A study assessed ChatGPT's strengths and weaknesses in SE, breaking down AI model competencies into three categories: syntactic knowledge, understanding static behaviour, and dynamic behaviour comprehension (Ma et al., 2023). ChatGPT has also been found to be prone to "hallucination" or generating incorrect information when analysing code structures. These findings underscore the importance of verifying ChatGPT's outputs for SE applications, especially since codes generated by such models might be syntactically correct but still vulnerable. The ChatGPT performance depends upon the person using it. We will study whether ChatGPT directly impacts the performance of software developers.

Ma et al. (2023) consider the utility of ChatGPT as a digital assistant in the startup setting. Interviews were carried out with the entrepreneurs who have interacted with ChatGPT. It was found that ChatGPT plays a vital role in startup settings, helping in tasks such as brainstorming, research, language enhancement, and web development. The efficiency of ChatGPT is based on its capabilities and how users engage with it. The prompting technique is essential because the output depends upon the quality of user prompts. This study aimed to analyse the complex behaviour of Software developers toward ChatGPT.

### *Hypothesis Development*

Davis and Davis (1989) and Venkatesh et al. (2003) have explained performance expectancy as self-belief that using technologies like ChatGPT will increase their effectiveness in tasks or goals. Maher (2020) found that performance expectancy is a key determinant when dealing with technology. Similar studies have also shown a moderately high correlation between performance expectancy and behavioural intention. Further, the research, including that by partners (Ma et al., 2023) and Shahsavar and Choudhury (2023), has made the relation between performance expectancy and learner willingness to adopt new learning techniques with the help of technology. For example, Ma et al. (2023) reflect that ChatGPT is an excellent tool for identifying and debugging errors in code, and Shahsavar and Choudhury (2023) studied the impact factors on users' perceptions of the decision-making process, as well as willingness to use ChatGPT for selfdiagnosing. Performance expectancy would explain the Software Developer's confidence that ChatGPT can increase their coding skills and output quality. We suggest the following hypothesis:

***H1: Performance expectancy has an impact on the Behavioural Intention***

"Effort expectancy" tells how much an individual believes that using a technology will make their efforts less (Moore & Benbasat, 1991; Venkatesh et al., 2003). Contemporary studies have emphasised the significant influence of "Effort expectancy" on Software developers ' willingness or "behavioural intention" to embrace various AI-assisted programming. Bernabei et al. (2023) showed the crucial role of Effort Expectancy in the field of learning, and (Ma et al. (2023) showed how ChatGPT reduces the efforts in bug solving. Similarly, Intiser et al. (2023) pinpointed the impact of Effort Expectancy when considering specific tools that help one to write. In the realm of research, "Effort expectancy" would define how much software developers perceive ChatGPT as user-friendly and how little effort they feel is needed to engage with it. Based on this, the following hypothesis is suggested:

***H2: Effort expectancy has a direct and significant impact on Behavioural Intention***

"Facilitating conditions" relates to how an individual feels they have the necessary resources and support to efficiently use a specific technology(Taylor & Todd, 1995)(Venkatesh et al., 2003). Research shows that "Facilitating conditions" is a crucial factor affecting learners' "behavioural intention" and actual "Use behaviour." It is highlighted as one of the primary influences on a person's technology adoption. Moreover, the importance of "Facilitating conditions" has been underscored in the context of adopting ChatGPT, such as bug-solving (Ma et al., 2023) and e-learning adoption in the era of the COVID-19 pandemic(Osei et al., 2022). Within this framework, "Facilitating conditions" would mean software developers' perception of their ability to access the AI tool even when it is in high demand and the extent of technical assistance and ChatGPT training they have at their disposal. Based on this understanding, we put the following hypotheses:

***H4: Facilitating conditions have an impact on Behavioural Intention***
***H5: Facilitating conditions have an impact on Use Behaviour***

"Hedonic motivation" describes the extent to which an individual is driven to apply a selected technology because of its inherent laugh, delight, or novelty elements (van der Heijden, 2004) (Venkatesh et al., 2012). Studies underscore that "Hedonic motivation" drives era adoption within numerous spheres (Ma et al., 2023) and that "Hedonic motivation" is an important component for resolving bugs using ChatGPT. In a similar fashion, (Agossah et al., 2023) gave importance to how it affects IT staff members' acceptance of their beliefs. In the context above, "Hedonic motivation" could gauge how much software developers find using ChatGPT enjoyable or satisfying, as well as how much they enjoy learning about new AI-powered technological solutions. These revelations lead to the proposal of the following hypothesis:

***H6: Hedonic motivation has a direct and significant impact on Behavioural Intention***

"Habit" pertains to how an individual's engagement with a specific technology becomes automatic or deeply embedded in their regular behaviours (Limayem et al., 2007)(Venkatesh et al., 2012). Studies reveal that Habit is instrumental in shaping learners' "behavioural intention" regarding technology usage. This is particularly evident in Adoption challenges (Sharma et al., 2023). There are a few theories related to software developers making a habit of using ChatGPT. However, there is much research in the learning setting, e.g. Nikolopoulou et al. (2020) identified the influence of Habit on adopting e-learning platforms. In the research context, "Habit" describes how deeply learners have incorporated ChatGPT into their learning activities. By understanding, we put the following hypothesis.

***H7: Habit has an impact on Behavioural intention***
***H8: Habit has a direct and significant impact on the Use Behaviour***

"Personal innovativeness" explains the individual's capability to get used to a new technology. The research found that personal innovativeness is an important aspect of the UTAUT2 model. For instance, (Kopplin, 2023) demonstrated that Personal innovativeness has a notable effect on the embrace of chatbots in the workplace. Likewise, (Russo, 2024) pointed to Personal innovativeness as a pivotal determinant in the complexity of Generative AI in software engineering. In the scope of this study, Personal innovativeness would refer to software developers' eagerness to welcome innovative tech solutions like ChatGPT, coupled with their self-belief in picking up and mastering novel technological proficiencies. On this basis, the subsequent hypothesis is suggested:

***H9: Personal innovativeness has a direct and significant impact on Use Behaviour***

"Behavioural intention" denotes an individual's perceived probability or commitment to adopt a specific technology in the foreseeable future, as suggested by (Davis and Davis, 1989) and (Venkatesh et al., 2012). In the context of software engineering, "Behavioural intention" quantifies the extent to which learners anticipate utilising ChatGPT. It's a pivotal predictor of actual tech utilisation and is shaped by other factors within the UTAUT2 framework. "Use behaviour", as outlined by (Venkatesh et al., 2003), indicates the real-world application of a technology post forming a behavioural intention towards it. For this research, "Use behaviour" encompasses frequency, duration, usage patterns, and the extent of ChatGPT utilisation in software engineering. Habitual usage also plays a part in influencing this behaviour.

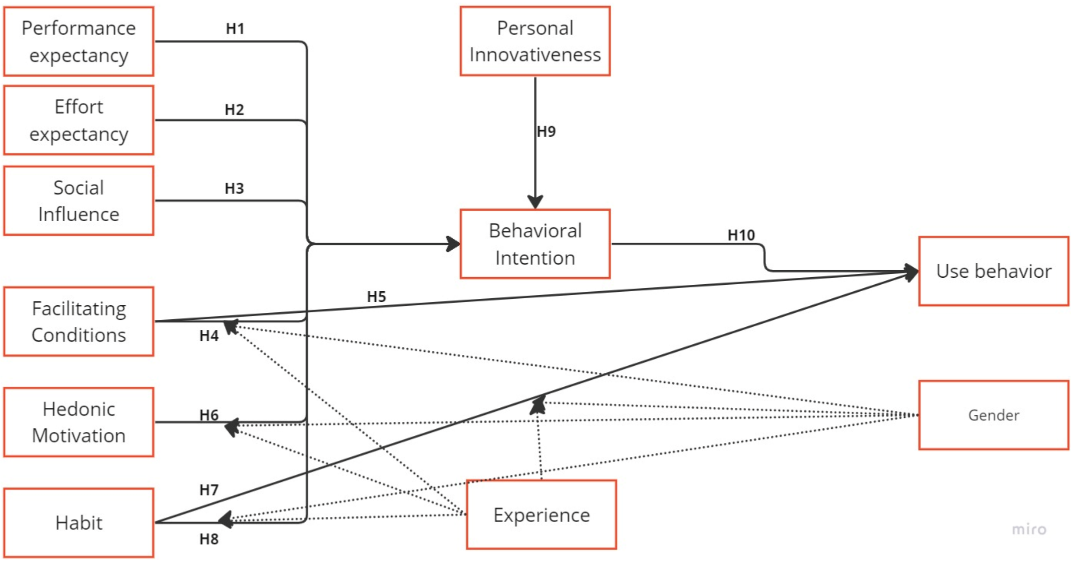


***Figure 1: Proposed Research Framework***

This research incorporates " Experience " and "Gender" as potential moderating elements that might alter the connection between the model's predictors and both the "Behavioural intention" and "Use behaviour" associated with ChatGPT(Ma et al., 2023). Due to the challenges in assessing the original "Experience" moderator, particularly given ChatGPT's relatively recent introduction to the public, we are considering the total work experience of a developer. The "Gender" remains consistent with the foundational theory(Ma et al., 2023), and we will concentrate on their work experience. The proposed theoretical framework can be viewed in Figure 1, featuring seven determining factors—six from the original UTAUT2 model and an added factor, "Personal Innovativeness".

## Research Methodology

Beginning in early April 2024, the survey was made available for six weeks to software developers via email addresses delivered directly to them via Microsoft Forms. A total of 335 legitimate answers were gathered. The judgemental sampling method was used to collect the data as this approach allows for the selection of participants who possess specific expertise or experience. Software developers, particularly those already familiar with AI tools like ChatGPT, can provide more meaningful insights into the factors that affect the acceptance and usage of ChatGPT in development workflows. Judgmental sampling enables focusing on participants who have relevant knowledge, ensuring the collection of high-quality data that is directly relevant to understanding the specialised aspects of ChatGPT integration, such as efficiency gains, potential challenges, and impact on productivity.

### *Measurement Scale*

Data was collected using a seven-point Likert scale, offering respondents choices from "strongly disagree" to "strongly agree". We employed a scale with seven options to evaluate use behaviour, from "never" to "several times a day". A numerical scale from 1 to 7 was established for consistent model estimation. Specifically, the scale was defined as: "Never" (1), "Once a month" (2), "Several times a month" (3), "Once a week" (4), "Several times a week" (5), "Once a day" (6), and "Several times a day" (7).

Our study included 30 items in total. Eighteen of these were adapted from (Venkatesh et al., 2003)(Venkatesh et al. 2012) that formulated the UTAUT and UTAUT2 frameworks. The original items discussed "system use" and "mobile internet use"; we tailored these to focus on "ChatGPT usage." Four items under "Performance expectancy" and "Effort expectancy" centred on ChatGPT's application. "Social influence" is represented by three items, "Facilitating conditions" and "Behavioral intention" have 4 and 3 items, respectively, drawn from the 2003 UTAUT version. Meanwhile, both "Hedonic motivation" and "Habit" comprise 3 and 4 items as outlined in the 2012 UTAUT2 edition. "Use behaviour" is gauged with a single item on a 7-option scale, capturing ChatGPT's usage frequency. Notably, (Venkatesh et al., 2012) did not specify their "Use behaviour" measurement method. The last four items were sourced from (Agrawal and Prasad's 1998) research.

## Table 1: Measurement Scale

| Construct | Code | Items | Item Loading | Source |
|---|---|---|---|---|
| Performance expectancy | PE1 | "I believe that ChatGPT is useful in my software development work." (Note: This item was marked as dropped but adapted for context.) | 0.725 | (Venkatesh et al., 2003, 2012) |
| | PE2 | "Using ChatGPT increases your chances of solving coding problems efficiently." | 0.785 | |
| | PE3 | "ChatGPT helps you get coding tasks and development projects done faster." | 0.777 | |
| | PE4 | "Using ChatGPT increases your productivity in software development." | 0.685 | |
| Effort expectancy | EE1 | "Learning how to use ChatGPT is easy for me | 0.403 | (Venkatesh et al., 2003, 2012) |
| | EE2 | "My interaction with ChatGPT is clear and understandable when seeking programming solutions." | 0.703 | |
| | EE3 | "I find ChatGPT easy to use for coding assistance and debugging." | 0.854 | |
| | EE4 | "I can easily learn how to use ChatGPT for coding." | 0.779 | |
| Social influence | SI1 | "People who are important to me think I should use ChatGPT in my development work." | 0.839 | (Venkatesh et al., 2012) |
| | SI2 | "People who influence my work behaviour believe I should use ChatGPT for coding." | 0.862 | |
| | SI3 | "People whose opinions I value prefer me to use ChatGPT for software development." | 0.847 | |
| Facilitating conditions | FCI | "l have the resources necessary to use ChatGPT" | 0.784 | (Venkatesh et al., 2003, 2012) |
| | FC2 | "l have the knowledge necessary to use ChatGPT" | 0.865 | |

| | | | | |
|---|---|---|---|---|
| | FC3 | "ChatGPT is compatible with the development tools and technologies I use." | 0.826 | |
| | FC4 | "I can get help from others when I have difficulties using ChatGPT in development." | 0.459 | |
| Hedonic motivation | HMI | "Using ChatGPT for coding is fun." | 0.909 | (Venkatesh et al., 2012) |
| | HM 2 | "Using ChatGPT for software development is enjoyable." | 0.928 | |
| | HM 3 | "Using ChatGPT for programming tasks is very entertaining." | 0.887 | |
| Habit | HT1 | "ChatGPT has become a habit in my development workflow." | 0.871 | (Venkatesh et al., 2012) |
| | HT2 | "I am addicted to using ChatGPT to solve development challenges." | 0.869 | |
| | HT3 | "I must use ChatGPT for my software development tasks." | 0.895 | |
| | HT4 | "Using ChatGPT has become a natural part of my coding process." | 0.888 | |
| Behavioural Intention | Bl1 | "I intend to continue using ChatGPT in my software development work in the future." | 0.909 | (Venkatesh et al., 2012) |
| | BI2 | "I will always try to use ChatGPT in my software development projects." | 0.896 | |
| | BI3 | "I plan to continue to use ChatGPT frequently in my coding tasks." | 0.911 | |
| Personal Innovativeness | PI1 | "I like experimenting with new information technologies in software development." | 0.725 | (Agrawal & Prasad, 1998) |
| | PI2 | "If I heard about a new information technology, I would look for ways to experiment with it in my development projects." | 0.785 | |
| | PI3 | "Among my colleagues/friends, I am usually the first to try new development tools and technologies." | 0.777 | |
| | PI4 | "In general, I do not hesitate to try out new information technologies for software development." | 0.685 | |

| | | | | |
|---|---|---|---|---|
| Use Behaviour | UB1 | "Please choose your usage frequency for ChatGPT in your development work: Never; Once a month; Several times a month; Once a week; Several times a week; Once a day; Several times a day." | 0.890 | (Venkatesh et al., 2012) |

### *Sample Size*

Choosing a suitable sample size is crucial for Partial Least Squares Structural Equation Modeling to guarantee the findings' reliability and correctness. The number of latent variables and indicators, the complexity of the model, the size of the expected effects, and the required statistical power are some of the criteria that determine the ideal sample size for PLS-SEM(Hair et al., 2013). Some experts suggest a minimum sample size of 100–200 observations, while others advocate for a sample size to indicator ratio of at least 5:1 or 10:1(Kock, 2018). Because this investigation included 30 indicators, a significant sample size of 335 observations was necessary (Table 1).

## Data Analysis

A total of 335 legitimate answers were gathered. There were 250 male software developers (74.6%) and 85 female software developers (25.4%) in the sample. With 65 entry-level developers (19.4%), 115 mid-level developers (34.3%), 80 senior developers (23.9%), and 75 developers with more than 6 years of experience (22.4%), the respondents' professional experience varied. The respondents employed a range of technologies: 155 utilised Javascript/Typescript (46.3%), 70 employed other technologies (20.9%), 60 employed Java (17.9%), and 50 employed Python (14.9%).

We used the Partial Least Squares Structural Equation Modeling technique using the SmartPLS 4 software (Version 4.0.9.1) to estimate the structural equation model. A maximum of 3000 iterations of the path weighting scheme and default initial weight settings were used for the model estimate. By the recommended standards described by (Sarstedt et al., 2022), we used the bootstrapping approach using 5000 bootstrap samples to evaluate the statistical significance of the model's path coefficients.

The indicator loadings of reflective constructs were used to validate them. A benchmark indicator loading of more than 0.7 indicates that the construct accounts for more than 50% of the indicator's variation, indicating satisfactory item dependability. The factor loadings of the model show that the items are reliable. However, we removed one item of Performance expectancy because factor loading was less than 0.5. This resulted in a modified model with 29 items in total. After removing the item, the model's overall reliability and validity were upgraded. The Effort expectancy, less than 0.5, has now increased to 0.61.

**Table 2: Reliability Analysis**

| | Cronbach's Alpha | Composite Reliability (rho_a) | Average Variance Extracted (AVE) |
|---|---|---|---|
| Behavioural Intention | 0.890 | 0.895 | 0.820 |
| Effort Expectancy | 0.685 | 0.731 | 0.611 |
| Facilitating Conditions | 0.723 | 0.774 | 0.564 |
| Hedonic Motivation | 0.894 | 0.898 | 0.824 |
| Habit | 0.904 | 0.906 | 0.776 |
| Performance Expectancy | 0.692 | 0.711 | 0.615 |
| Personal Innovativeness | 0.735 | 0.754 | 0.554 |
| Social Influence | 0.808 | 0.812 | 0.721 |

The consistency and validity were checked with the help of Average Variance Extracted (AVE), Composite Reliability (ρ_a), and Cronbach's Alpha. The value lies between 0.70 and 0.95, and AVE is more than 0.5, as suggested by (Sarstedt et al., 2022). All latent variables met the quality requirements.

The Heterotrait-Monotrait correlation ratio used to determine the discriminant analysis (Henseler et al., 2015) suggested a threshold of 0.90 for comparable constructs and a more severe 0.85 for dissimilar constructs. All HTMT values are below 0.85, which highlights no issue of multi-collinearity.

**Table 3: Heterotrait-Monotrait Ratio**

| | BI | EE | FC | HM | HT | PE | PI | SI | UB1 |
|---|---|---|---|---|---|---|---|---|---|
| BI | | | | | | | | | |
| EE | 0.806 | | | | | | | | |
| FC | 0.76 | 0.728 | | | | | | | |
| HM | 0.724 | 0.729 | 0.67 | | | | | | |
| HT | 0.614 | 0.738 | 0.665 | 0.668 | | | | | |
| PE | 0.75 | 0.788 | 0.674 | 0.698 | 0.48 | | | | |
| PI | 0.635 | 0.722 | 0.748 | 0.62 | 0.311 | 0.663 | | | |
| SI | 0.699 | 0.787 | 0.615 | 0.627 | 0.696 | 0.717 | 0.422 | | |
| UB1 | 0.594 | 0.578 | 0.488 | 0.472 | 0.475 | 0.605 | 0.436 | 0.479 | |

The R-squared ($R^2$) values represent the percentage of dependent variables' variance that the structural model explains and was obtained through examination of the model. We computed the effect size (f2) of the variables to measure the influence of each predictor; minor, medium, and significant impacts were represented by values of 0.02, 0.15, and 0.35, respectively.

Based on the structural model analysis, facilitating conditions (FC), with a path coefficient of 0.205, and Hedonic motivation (HM), with a coefficient of 0.198, were found to be the strongest predictors of Behavioral Intention (BI). These variables significantly reduced the variance in BI, suggesting that facilities and the perceived convenience of ChatGPT play a critical role in encouraging the desire to utilise it for software development tasks. With a coefficient of 0.419, Behavioral Intention (BI) to Use Behavior (UB1) had the most significant effect and explained 56.3% of the variance in Use Behavior.

The hypothesised and evaluated moderating effects of "Gender" and "Experience" did not significantly impact the connection between the predictors and dependent variables. This lack of significance shows that these demographic factors do not significantly influence the intention or usage behaviour toward ChatGPT for software development. Table 4 provides a complete summary of the path coefficient results, significance tests, and hypothesis confirmation. The lack of significant benefits for some paths, like the impact of Facilitating Conditions on Use behaviour (H5) and the impact of Habit on Behavioral intention(H7), draws attention to the complex dynamics of software developers' technology adoption and indicates areas requiring more research.

***Direct Effect***

Table 4 presents the results of path analysis, showing the relationships between various constructs and their impact on Behavioral Intention (BI) and Usage Behavior (UB1). Each path is described with the estimated coefficient (Path Estimates), standard deviation, t-statistic, and p-value.

The path from Performance Expectancy (PE) to BI has an estimate of 0.145 with a t-statistic of 2.704 and a p-value of 0.007, indicating a statistically significant positive effect. Effort Expectancy (EE) to BI has a stronger effect with an estimate of 0.177, a t-statistic of 2.864, and a p-value of 0.004, also showing statistical significance. Social Influence (SI) influences BI with an estimate of 0.152, a t-statistic of 3.417, and a p-value of 0.001, which is significant. Facilitating Conditions (FC) shows an even stronger effect on BI with an estimate of 0.205, a t-statistic of 3.690, and a p-value of 0.000, marking high significance.

When considering Facilitating Conditions' effect on Usage Behavior (UB1), the estimate is lower at 0.062, with a t-statistic of 1.245 and a p-value of 0.213, indicating it is not statistically significant. Hedonic Motivation (HM) has a significant positive effect on BI, with an estimate of 0.198, a t-statistic of 2.816, and a p-value of 0.005. Habit (HT) impacts BI with an estimate of 0.057, though this effect is not statistically significant (p-value of 0.170). However, HT significantly affects UB1 with an estimate of 0.187, a t-statistic of 3.832, and a p-value of 0.000. Price Value (PI) has a modest but significant impact on BI, with an estimate of 0.107, a t-statistic of 2.241, and a p-value of 0.025.

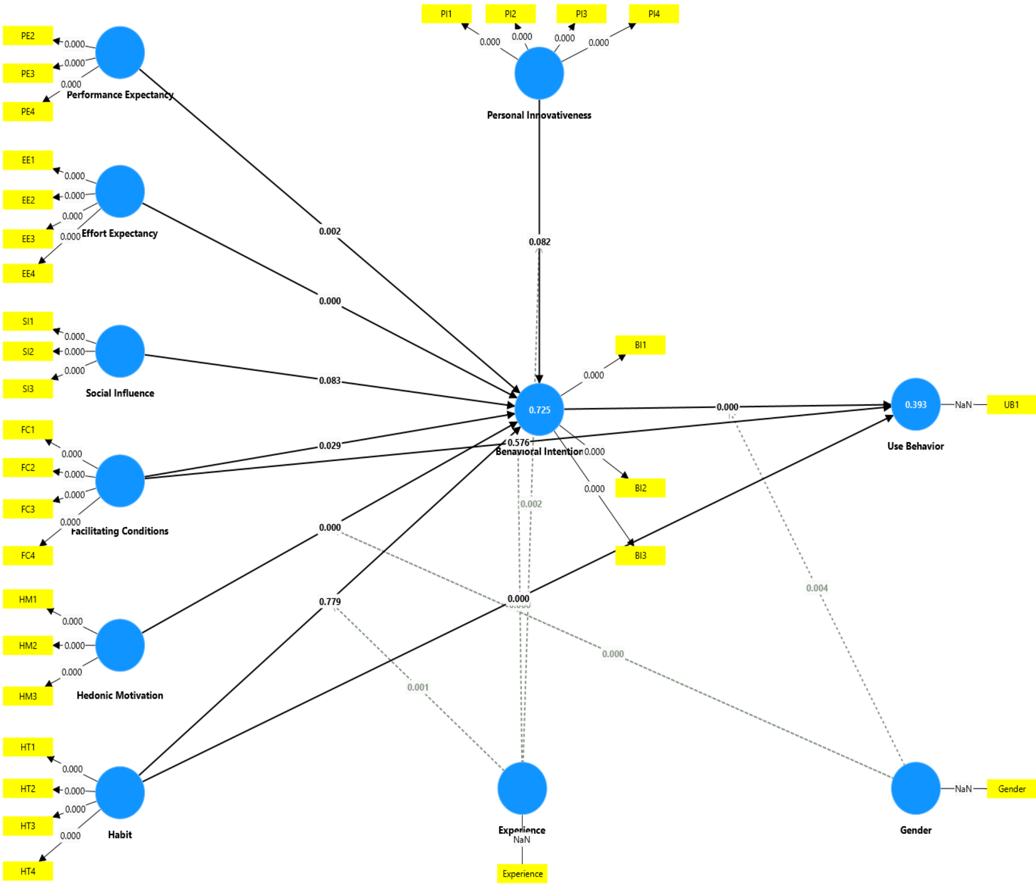


***Figure 2: Measurement Model***

Finally, Behavioral Intention (BI) strongly influences Usage Behavior (UB1) with an estimate of 0.419, a t-statistic of 9.163, and a p-value of 0.000, indicating a highly significant positive relationship.

**Table 4: Direct Effect**

| Path | Estimates | Standard Deviation | T statistics | P values |
|---|---|---|---|---|
| PE → BI | 0.145 | 0.053 | 2.704 | 0.007 |
| EE → BI | 0.177 | 0.062 | 2.864 | 0.004 |
| SI → BI | 0.152 | 0.045 | 3.417 | 0.001 |
| FC → BI | 0.205 | 0.055 | 3.690 | 0.000 |
| FC → UB1 | 0.062 | 0.050 | 1.245 | 0.213 |
| HM → BI | 0.198 | 0.070 | 2.816 | 0.005 |
| HT → BI | 0.057 | 0.042 | 1.374 | 0.170 |
| HT → UB1 | 0.187 | 0.049 | 3.832 | 0.000 |
| PI → BI | 0.107 | 0.048 | 2.241 | 0.025 |
| BI → UB1 | 0.419 | 0.046 | 9.163 | 0.000 |

Table 5 displays the moderating effects of various interactions on Behavioral Intention (BI) and Use Behavior (UB), with the results presented as the original sample estimate (O), T statistic, and p-value for each interaction.

The interaction between Experience and Habit on BI has a negative effect, with an estimate of -0.076, a T statistic of 3.289, and a p-value of 0.001, indicating that as Experience and Habit interact, their combined effect reduces BI significantly. The interaction between Gender and BI on UB shows a negative estimate of -0.101, a T statistic of 2.913, and a p-value of 0.004, suggesting that Gender moderates the impact of BI on UB in a way that slightly lowers this effect.

The interaction of Gender and Hedonic Motivation on BI exhibits a strong negative moderating effect, with an estimate of -0.267, a very high T statistic of 8.56, and a p-value of 0.000, indicating that Gender significantly diminishes the effect of Hedonic Motivation on BI. In contrast, the interaction between Experience and Personal Innovativeness on BI is positive, with an estimate of 0.075, a T statistic of 3.136, and a p-value of 0.002, showing that Personal Innovativeness strengthens the impact of Experience on BI.

Finally, the interaction between Experience and Facilitating Conditions on UB has a positive estimate of 0.169, a high T statistic of 4.81, and a p-value of 0.000, indicating a strong and significant positive moderating effect, where Experience enhances the influence of Facilitating Conditions on UB.

**Table 5: Moderating Effect**

| | Original sample (O) | T statistics | P values |
|---|---|---|---|
| Experience x Habit -> Behavioral Intention | -0.076 | 3.289 | 0.001 |
| Gender x Behavioral Intention -> Use Behavior | -0.101 | 2.913 | 0.004 |
| Gender x Hedonic Motivation -> Behavioral Intention | -0.267 | 8.56 | 0.000 |
| Experience x Personal Innovativeness -> Behavioral Intention | 0.075 | 3.136 | 0.002 |
| Experience x Facilitating Conditions -> Use Behavior | 0.169 | 4.81 | 0.000 |

### *Discussion*

Our study adds another insight into how software developers use ChatGPT to further their work. Our study offers new perspectives on the adoption and application of AI chat technology as a tool for professional growth, whereas the majority of prior research has focused on educational environments. In order to assess ChatGPT adoption, we used the UTAUT2 framework, which was strengthened with "Personal innovativeness." We ensured that each of the seven constructs satisfied the requirements for validity and reliability. As per (El-Masri & Tarhini, 2017) findings on users' acceptance of e-learning systems, our analysis validates the positive correlation between "Performance expectancy," "Hedonic motivation," and "Behavioral intention."

As per our research, software developers are more likely to use ChatGPT when they see the benefits of increasing their productivity when they use it frequently. These results confirm the assertions made by (Venkatesh et al., 2012), while (Yu et al., 2021) found matching trends, underlining the crucial roles that "Effort expectancy" and " Facilitating Conditions" play in the adoption of new technologies. However, our data show that "Habit" has a practical consequence on "Use behaviour," which is consistent with research by (Ma et al., 2023). This indicates that, in software development, the ChatGPT may not be added to the routine, and its usefulness is still under question.

Our result departs from other studies, such as those by (Mehta et al., 2019), in that it highlights the pleasure and fun (also known as "Hedonic motivation") that software developers have when they communicate with ChatGPT. Developers prefer exciting and innovative tools and ChatGPT's conversational, user-friendly design appeals to their preferences. This is an essential aspect in the field where learning new things constantly and adapting to technology are needed. In a nutshell, developers understand when it is a complex problem; they also need to give proper prompts so that ChatGPT can generate valid output. It may take multiple iterations to get the valid output, just like debugging an error. This similar pattern in both processes may encourage developers to use ChatGPT more.

"Habit" and "Personal Innovativeness" have a minor effect on "Behavioral intention." It might be due to hallucinating or generating incorrect information while analysing or debugging the code. The high mean values for "Effort expectancy" suggest that developers had fewer challenges when it came to integrating ChatGPT into the software development process. This is similar to the trend that tells about ChatGPT use in research on e-learning platforms (Nikolopoulou et al., 2020) and technology use in software development (Nguyen & Nadi, 2022)

Software developers may have much weight on the opinions of people in their professional group when making decisions about implementing new technologies, as evidenced by the impact of "Social influence" on the "Behavioral intention" to utilise ChatGPT. This is in alignment with situations where "Social influence" has been demonstrated to be important in the adoption of technology, including mobile devices and mobile learning (Ameri et al., 2020).

In support of research findings by (Ameri et al., 2020) and (Arain et al., 2019), where "Facilitating conditions" did have an impact on "Behavioral intention." Our study demonstrates that "Facilitating conditions" moderately impact "Use behaviour." This gives the idea that, despite the availability and ease of use of ChatGPT, it may not affect software developers' intent to use it. The underlying aspects are important in real-world behaviour when using technology.

The moderating variables like gender and experience have a complex way of affecting peoples' adoption of technology. For example, the negative interaction between experience with habit and behavioral intention ($p = 0.001$) implies that frequent usage of ChatGPT does not always imply an intention to utilise it more for seasoned software developers. Conversely, there appears to be a tendency among more seasoned developers to investigate and use novel technologies, as indicated by the noteworthy positive correlation between experience and Personal Innovativeness ($p = 0.002$).

The study makes a substantial contribution to the literature with its unique focus on ChatGPT inside software development. This field is comparatively understudied in comparison to its use in education. The knowledge gained here could help direct the incorporation of AI technologies such as ChatGPT into software development procedures, enhancing the resources and techniques available to developers and the companies they work with.

## *Conclusion*

Our comprehensive examination of software developers' use of ChatGPT has validated the accuracy and consistency of our measurement models, emphasising the distinct predictive correlations established by the UTAUT2 framework. Significant effects of Effort Expectancy, Hedonic Motivation, and Facilitating Conditions on Behavioral Intention are among the key findings that point to a complex motivational framework for technology adoption in software development. The topic of using AI in software development is still in its infancy, even though our sample of developers was diversified in terms of their backgrounds and areas of expertise. Thus, to improve the scales' accuracy and applicability even further, future research should review and improve the ones employed in this study. This study validates the UTAUT2 model as a valuable instrument for evaluating the adoption of new technologies, which is essential for promoting innovation in the quickly changing software industry.

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