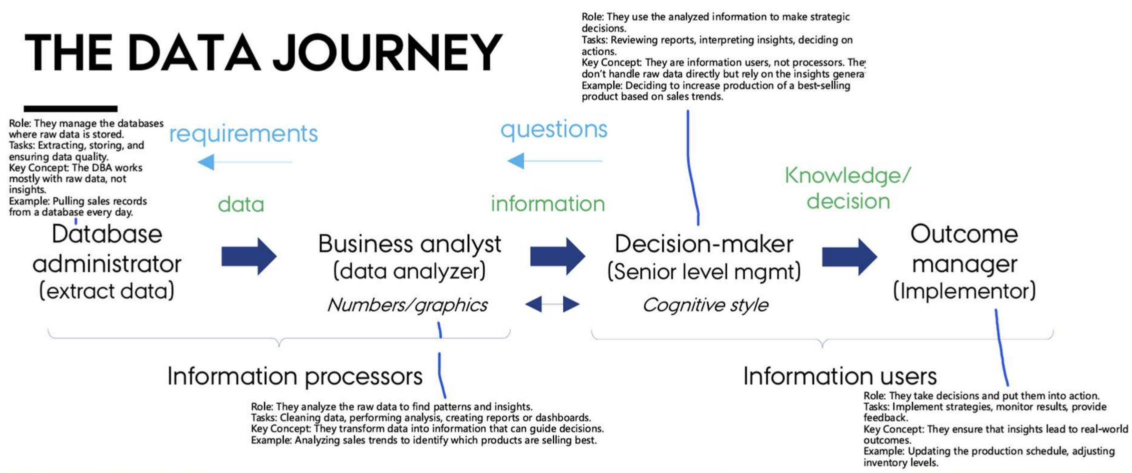
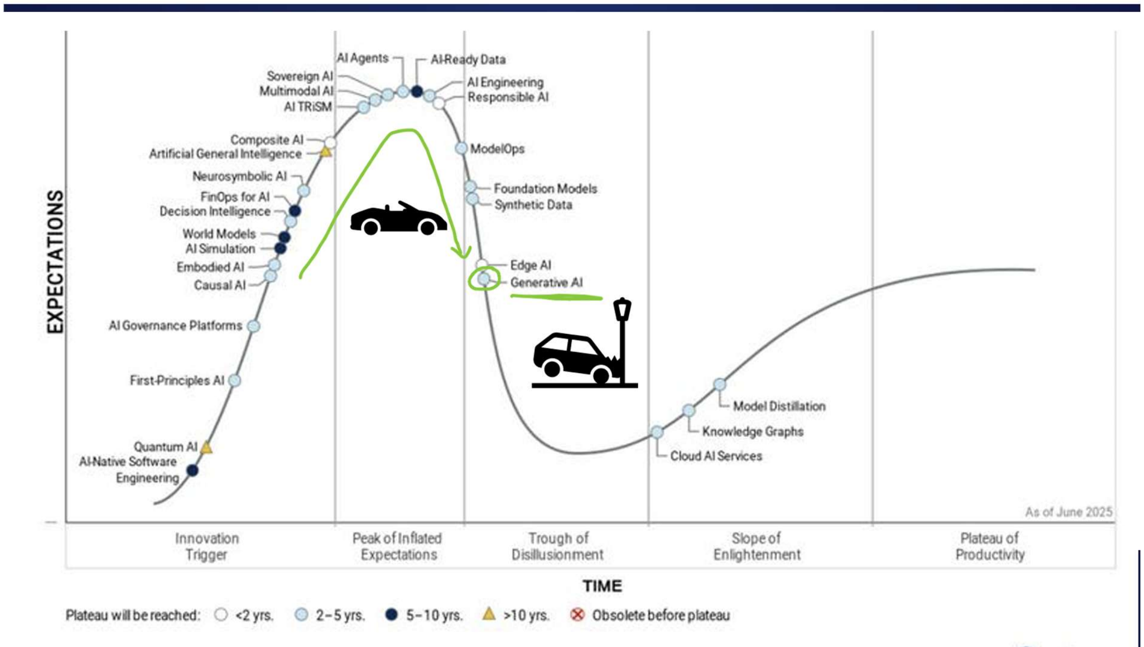
# Technology accaptance and use

## Going tot he individual Level



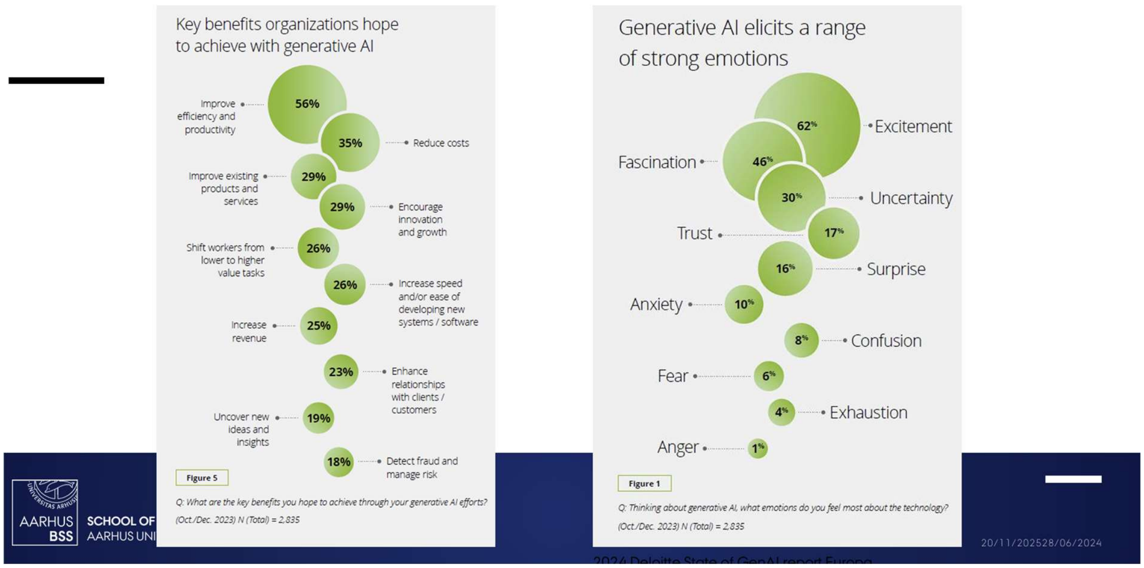

The slide presents the Gartner Hype Cycle for AI, which describes how new technologies move through stages of expectations over time. At the beginning, innovative ideas emerge and attract attention, rising quickly toward the Peak of Inflated Expectations, where excitement and unrealistic promises are at their highest. This is illustrated on the slide by a car racing up the curve, symbolizing the rapid hype and momentum surrounding emerging AI concepts such as AGI, AI agents, and multimodal AI models.

After reaching this peak, technologies inevitably begin to fall into what is called the Trough of Disillusionment. Here, people realize that the technology cannot immediately deliver on all the high expectations. The green arrow and the small circled dot on the slide highlight this transition, showing how Generative AI and Edge AI have now entered this phase. The crashed car at the bottom visually represents this decline in enthusiasm as organizations confront limitations, challenges, and the real-world effort required to implement these systems effectively.

Despite this downturn, the Hype Cycle shows that technologies do not remain in the trough. As companies learn how to use them properly, they begin moving up the Slope of Enlightenment, where practical understanding and productive use cases emerge. Eventually, the technology reaches the Plateau of Productivity, where its benefits are widely realized and it becomes a stable, mature part of business operations.

In summary, the slide uses cars and arrows as metaphors to show that many AI technologies are climbing or have reached the peak of hype, while Generative AI is now entering the more realistic phase of disillusionment before eventually maturing into stable and productive use.

# DIFFERENT VIEWS ON AI/BI IN THE ORGANIZATION




The slide illustrates how organizations perceive generative AI from two perspectives: the benefits they expect to gain and the emotions the technology triggers among employees and stakeholders. On the left side, the figure shows that most organizations hope generative AI will primarily help them improve efficiency and productivity, which 56% of respondents identified as the top benefit. Reducing costs is the second most common expectation, mentioned by 35%. Beyond these operational improvements, many organizations also expect AI to enhance their existing products and services and to encourage innovation and growth, each reported by 29%. About a quarter of the respondents believe AI will help shift workers from low-value to higher-value tasks, speed up system and software development, or increase revenue. Smaller but still significant groups see generative AI as a tool to uncover new ideas and insights, to enhance client relationships, or to detect fraud and manage risk. Overall, the results show that businesses view AI as both a productivity booster and an innovation driver.

The right side of the slide highlights that generative AI not only brings expectations but also evokes a wide range of emotions. The strongest emotion is excitement, felt by 62% of respondents, showing that people are energized by the possibilities AI creates. Fascination follows at 46%, indicating that many are intrigued and curious about the technology. However, enthusiasm is mixed with uncertainty, which 30% of respondents express, and surprise, reported by 17%. Trust is present but relatively low at 16%, while 10% feel anxiety. Smaller groups experience confusion, fear, exhaustion, or even anger. This emotional diversity demonstrates that while AI is seen as promising and innovative, it also brings concerns and questions about reliability, impact on jobs, and how it will be integrated into organizational life.

Together, the two charts show that generative AI generates high expectations but also emotional complexity. Organizations see AI as a major opportunity for efficiency, innovation, and growth, yet individuals simultaneously react with excitement, uncertainty, curiosity, and apprehension. The slide illustrates that adopting AI is not only a technical transformation but also a human one that involves both optimism and anxiety.

Intention to use

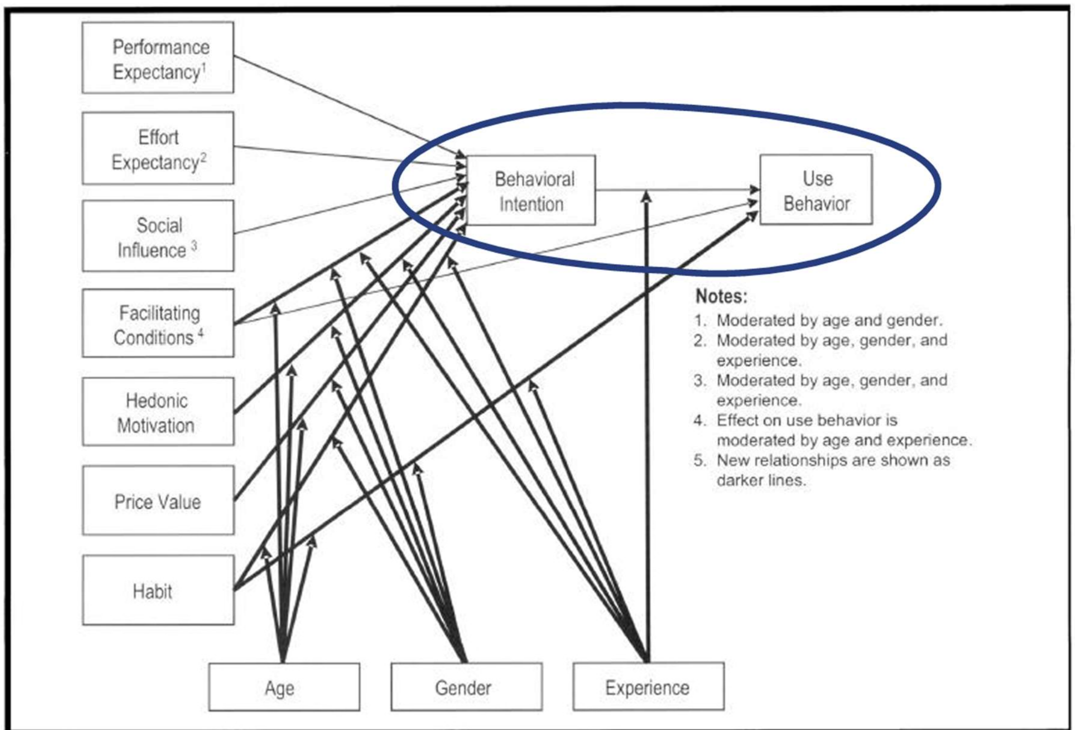


**Figure 1. Research Model: UTAUT2**

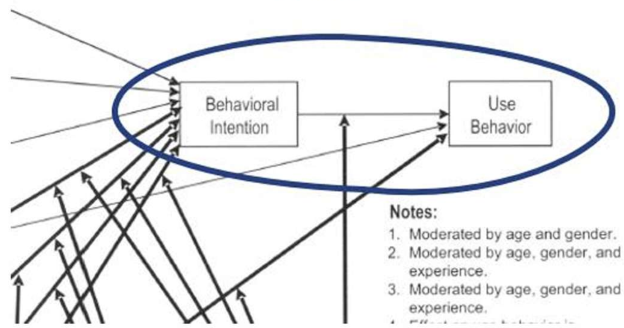
The circled area of the UTAUT2 research model highlights the central relationship between *behavioral intention* and *actual use behavior*. In this model, behavioral intention represents a person's willingness or motivation to use a technology—essentially how likely they are to adopt it. This intention is shaped by multiple factors, such as performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit. When these factors influence an individual positively, their behavioral intention increases.

The model assumes that a stronger behavioral intention leads directly to a higher likelihood of actual technology use. Therefore, the arrow from behavioral intention to use behavior represents this core predictive link: if people intend to use a system, they generally will. However, the model also acknowledges that certain factors, especially facilitating conditions and habit, can influence actual use directly, independent of intention. The circled section thus represents the heart of the adoption process, where intentions turn into real behavior. These relationships are moderated by variables such as age, gender, and experience, meaning that the strength of the connection can vary depending on demographic characteristics. Overall, this part of the model captures the essential idea that what people plan to do is usually a strong indicator of what they ultimately do when interacting with technology.

# PREVIOUS MODELS

- The ISS model
- The diffusion theory

Connected




Detailed Explanation: How ISS and Diffusion Theory Are Connected

Although the ISS model and Diffusion Theory come from different research traditions, they are connected through a shared central mechanism: both models explain that people's perceptions and attitudes shape their behavioral intention, which then determines whether they actually use an information system or innovation. In other words, both theories feed into the core link highlighted in the circled UTAUT2 area—*behavioral intention → use behavior*.

1. Information Systems Success (ISS) Model → Behavioral Intention

The ISS model focuses on whether an information system is considered successful by its users. Its key idea is that system success comes from three types of quality:

- System quality (Is it easy to use? Is it reliable?)
- Information quality (Does the system output useful, accurate information?)
- Service quality (Is support available and effective?)

These qualities influence:

- User satisfaction
- Perceived usefulness

Both of these lead directly to intention to use the system.

Thus, the ISS model is inherently an *intention-based* model:

good quality → satisfied users → intention → actual use.

This means that the ISS model provides an early psychological explanation of why people *intend* to adopt technology.

2. Diffusion of Innovation (Rogers) → Behavioral Intention

Diffusion Theory, in contrast, focuses on how *innovations spread through societies over time*. It describes the characteristics that make people more likely to adopt an innovation:

- Relative advantage (Is it better than what I had?)
- Compatibility (Does it fit my needs, values, workflows?)
- Complexity (How difficult is it to understand and use?)
- Trialability (Can I try it out easily?)
- Observability (Do I see others benefiting from it?)

These characteristics create positive or negative perceptions of the innovation.

These perceptions then shape the individual's intention to adopt it.

So, even though diffusion theory is often used at a population level, at the individual level it operates through beliefs → intention → adoption.

3. How ISS and Diffusion Theory Connect to Each Other

Even though ISS focuses on system quality and Diffusion Theory focuses on innovation traits, both models share these fundamental ideas:

A. Both explain adoption through cognitive evaluations

- ISS model → quality perceptions
- Diffusion theory → innovation attributes

  Both sets of perceptions shape the user's overall attitude.

B. Both lead to Behavioral Intention

In both theories, perceptions feed into a mental decision:

"Do I plan to use this system?"

ISS calls this *intention to use*.

Diffusion theory calls it *adoption intention*.

C. Both assume Intention → Actual Use

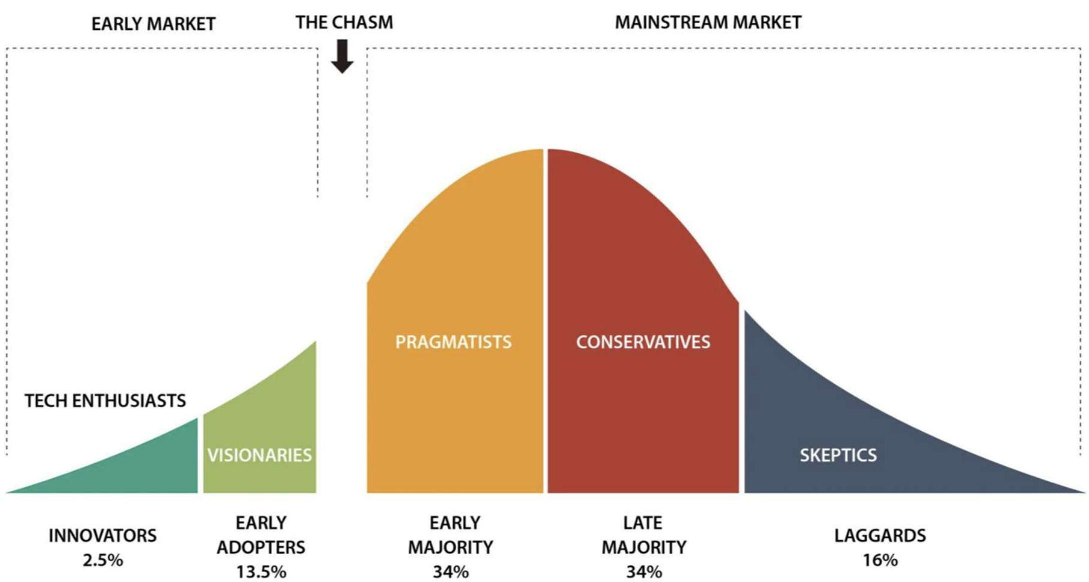
In both models, intention is the predictor of real behavior:
people use a system *because they intend to*, influenced by their perceptions.
D. Both include social influence indirectly

- ISS includes service quality, which includes support people.
- Diffusion theory includes observability and communication channels, which require social interaction.

So both agree that social factors affect intention.
4. How Both Models Connect to the Circled UTAUT2 Area
The circled area of UTAUT2 (Behavioral Intention → Use Behavior) is the unifying mechanism that both earlier models share. UTAUT2 essentially *absorbs* these earlier insights:

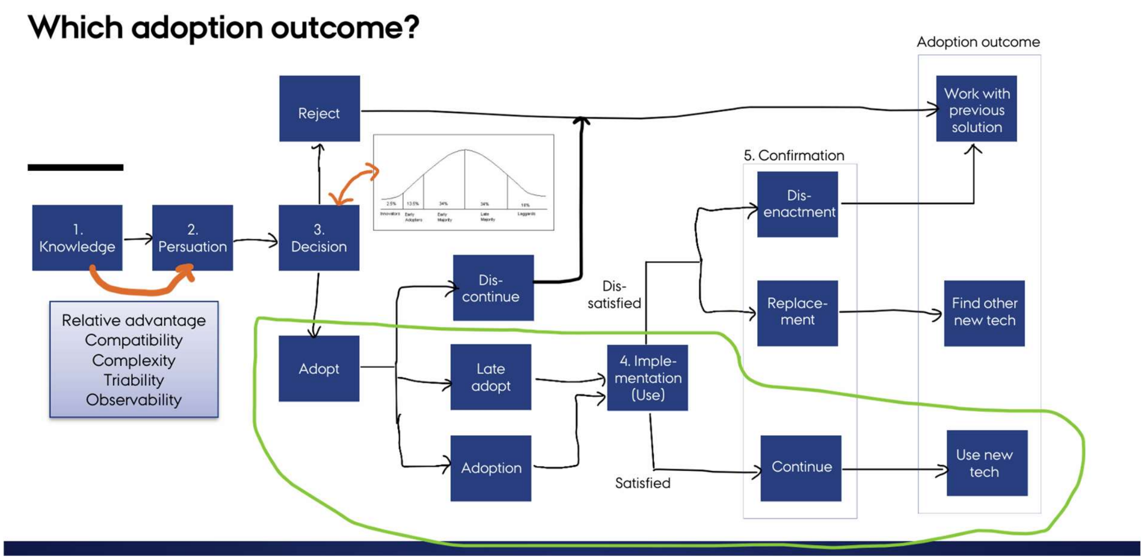
- From ISS, it takes the idea that quality and satisfaction shape intention.
- From Diffusion Theory, it takes the idea that perceived characteristics of technology shape intention and adoption.

UTAUT2 then integrates these influences into a broader set of constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, habit, etc.).
Thus:
ISS + Diffusion Theory → Behavioral Intention → Use Behavior
And UTAUT2 formalizes and extends this pathway.



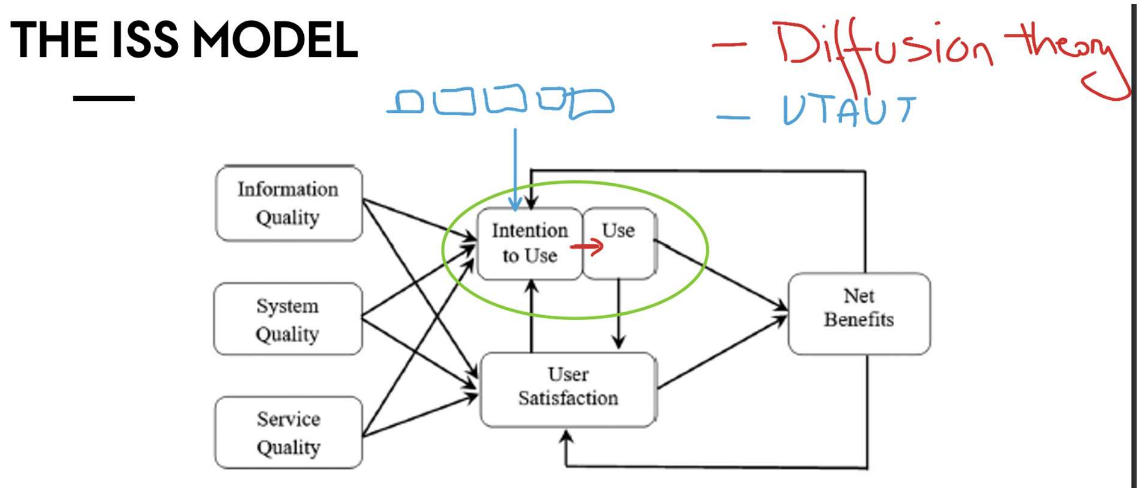

The slide illustrates the classic Technology Adoption Lifecycle, a model that explains how different groups of people adopt a new technology over time. The curve is divided into segments that represent distinct adopter categories, each with its own characteristics, motivations, and adoption speed. On the far left are the Innovators, who make up about 2.5% of the population. These individuals are tech enthusiasts who adopt new technologies simply because they enjoy experimenting with new ideas. They are driven by curiosity rather than clear business benefits.
Following them are the Early Adopters, sometimes called Visionaries. Representing roughly 13.5% of the population, they are not interested in technology for its own sake but for the strategic advantages it can deliver. They are willing to take risks and are often responsible for pushing new technologies into the mainstream by demonstrating their potential value.
Between the Early Adopters and the Early Majority lies the “chasm,” a critical gap that many innovations struggle to cross. The chasm represents the difficulty of moving from an early market, where people are willing to take risks, to a mainstream market, where people demand proven, reliable solutions. Many technologies fail at this stage because the expectations of early adopters differ dramatically from those of more pragmatic users.
On the other side of the chasm are the Pragmatists, forming the Early Majority and representing about 34% of the population. These users adopt a technology only once its benefits have been demonstrated and it has become stable and reliable. They do not take risks and rely heavily on references, success stories, and practical evidence.

Next comes the Late Majority, also 34% of the population. These Conservatives adopt technology primarily out of necessity, often because everyone else is already using it. They are skeptical and cost-sensitive, waiting until a technology becomes a standard or is unavoidable.
Finally, the curve ends with the Laggards, who make up about 16% of the population. Also called Skeptics, they resist adopting new technology until the very end, sometimes only when the old solution is no longer available. Their resistance can stem from habit, fear of change, or lack of resources.
Overall, the slide demonstrates how innovations spread unevenly across society and highlights the importance of understanding the chasm: the point at which a promising technology must shift from appealing to visionaries to convincing pragmatic users. Successfully crossing this gap is often what determines whether a new technology becomes widely adopted or fades away.



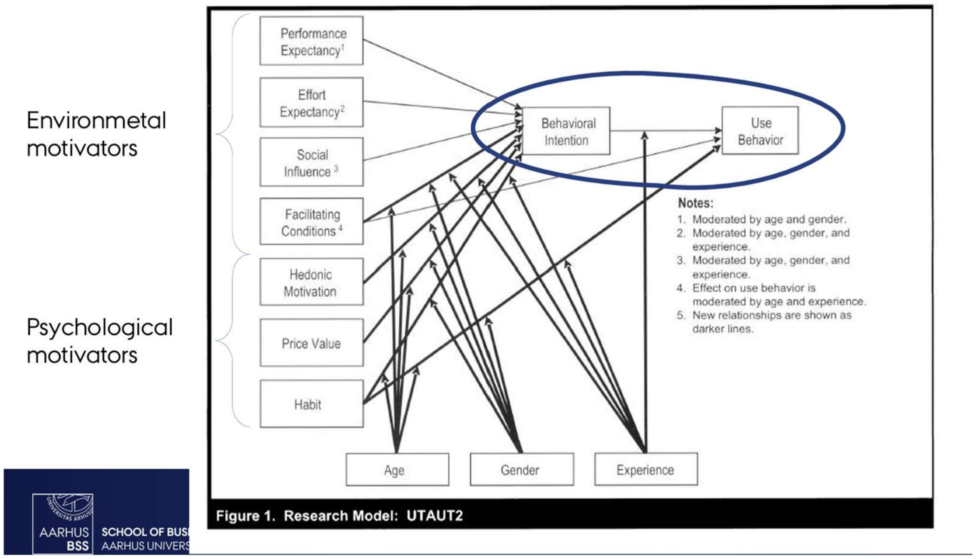

The slide illustrates the full process of technology adoption based on **Diffusion of Innovation theory**, from the moment a person first becomes aware of a new technology to the point where they either continue using it or abandon it. The process begins with the stage of *Knowledge*, where an individual becomes aware of the technology and forms an initial understanding of what it can do. This leads into the *Persuasion* stage, where their attitude toward the innovation develops. At this point, the person evaluates five key characteristics—relative advantage, compatibility, complexity, trialability, and observability. These factors strongly shape whether they will view the innovation positively or negatively.
Based on these perceptions, the individual enters the *Decision* stage. Here they choose either to adopt the technology or reject it. If they reject it, the process effectively ends, and they continue using their previous solution. If they adopt it, they move into implementation and actual use.
This is where the **green-circled part** of the slide becomes important. After adoption, people do not simply continue using the technology automatically. Instead, their relationship with the innovation can develop in multiple directions depending on their experience. During the *Implementation* stage, users try out the technology in practice. If the experience meets their needs and they are satisfied, they transition to the *Confirmation* stage, where they form a more stable commitment to the innovation. This positive path leads to continued use and eventually a stable outcome such as fully integrating and consistently using the new technology within their work — the box labeled *Use new tech*.
However, implementation can also expose problems. If users are dissatisfied, they may *discontinue* their use. This can happen early, right after adoption, or later during confirmation. Discontinuation can take two forms: *dis-enactment*, where users actively stop using the innovation and return to an older solution, or *replacement*, where they decide to search for another, better technology. In this case, the adoption process does not end completely; instead, users may re-enter the cycle but with a different innovation.

The model also includes a category for *late adoption*, acknowledging that some individuals only adopt after seeing others use it successfully. These late adopters follow the same implementation and confirmation steps, facing the same possible outcomes of continuation or discontinuation.
Altogether, the green-highlighted area represents all the possible adoption outcomes *after* a person has initially said "yes" at the decision stage. It emphasizes that **adoption is not a single event but a dynamic process**. The final outcome—whether someone continues using the new technology, replaces it, or returns to their previous solution—depends heavily on their satisfaction after actual use.




The ISS model explains how the success of an information system emerges through a chain of perceptions and behaviors that ultimately influence whether users continue to use a technology and whether organizations gain meaningful benefits from it. At the start of the model, three types of quality—information quality, system quality, and service quality—shape how users evaluate the system as they interact with it. When the information the system provides is accurate and relevant, when the system itself is reliable and easy to use, and when supporting services are helpful and timely, users form a positive overall experience. This experience directly contributes to their satisfaction with the system.
User satisfaction is an important psychological state in the model, because it feeds directly into the user's intention to use the system in the future. Intention to use is highlighted in the circled area of the slide because it represents the critical turning point between what users think and what they actually do. In the ISS framework, intention is the immediate precursor to actual system use. The model assumes that if users intend to use the technology, they will generally follow through and use it, and this actual usage then contributes to observable net benefits, such as improved decision-making, higher productivity, or cost efficiency. These benefits can feed back into satisfaction, reinforcing the cycle.
The circled section is also important because it is the conceptual point where the ISS model connects to other major theories of technology adoption, such as Diffusion Theory and UTAUT. In Diffusion Theory, individuals move from knowledge to persuasion and then to a decision based on their perceptions of relative advantage, compatibility, complexity, trialability, and observability. The outcome of this persuasion stage is essentially the same construct: a formed intention to adopt or reject the new technology. Similarly, UTAUT uses factors like performance expectancy, effort expectancy, social influence, and facilitating conditions to explain why a person develops the intention to engage with a system. In both models, just as in the ISS model, intention is the final psychological step before actual use is observed.
This is why the circled area is so central: it represents the universal mechanism that links all major technology adoption theories. Whether the focus is on system quality, innovation attributes, or user expectations, these inputs always culminate in a behavioural intention, which then drives actual system usage. In other words, the ISS model, Diffusion Theory, and UTAUT all converge on this same internal structure, where intention forms the bridge between psychological evaluation and real behavior. The

circled part therefore illustrates not only the core of the ISS model but also the conceptual point where all these models overlap.



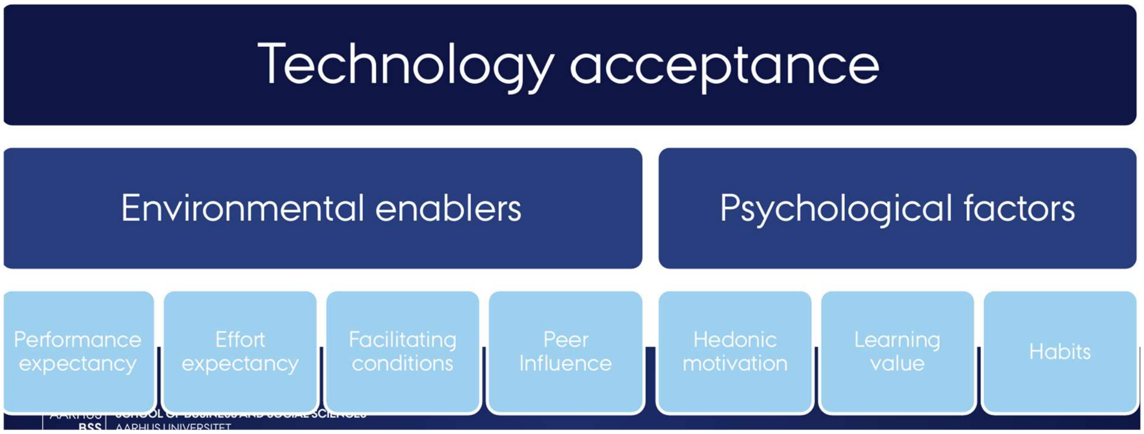

The slide presents the UTAUT2 model and highlights how different types of motivators shape a person's intention to use a technology, which in turn determines whether that person will actually use it. On the left side, the model distinguishes between environmental motivators and psychological motivators. Environmental motivators include performance expectancy, effort expectancy, social influence, and facilitating conditions. These reflect the external environment and the user's context: how useful they believe the system will be for achieving their goals, how easy it is to use, how much support or encouragement they experience from others, and whether the surrounding infrastructure makes usage possible. These factors come from outside the individual and represent the situational pressures or enablers that influence technology adoption.

Below them, the model includes psychological motivators such as hedonic motivation, price value, and habit. These represent the user's internal drivers: the enjoyment they get from using the technology, their evaluation of whether the cost feels justified by the benefits, and the extent to which using the technology has become an automatic behavior. Together, these motivators shape the user's internal state regarding the technology.

All these motivators converge on one central psychological construct, highlighted in the circled section of the slide: **behavioral intention**. This is the point where all influences—social, technological, cognitive, emotional, and contextual—are integrated into a single decision: the user's intention to use the system. Behavioral intention is therefore the mechanism through which both environmental and psychological motivators translate into future action. Once behavioral intention has been formed, the model assumes that this intention will largely determine the user's actual system use, unless moderated by their age, gender, or experience. These moderating variables can strengthen or weaken the influence of each motivator, explaining why some groups adopt technology more quickly or more easily than others.

The circled transition from behavioral intention to use behavior represents the core of the UTAUT2 logic. It marks the moment where psychological evaluation becomes observable behavior. This is the same mechanism found in earlier adoption theories such as Diffusion Theory and the ISS model, which also use intention as the bridge between attitudes and real-world usage. In UTAUT2, however, this bridge is enriched and made more realistic by acknowledging that different kinds of motivations—externally shaped conditions as well as internal emotional and habitual factors—jointly determine whether a person intends to use a technology. Ultimately, the circled area shows the model's claim that actual system use is not random but the natural outcome of a complex combination of environmental stimuli, psychological states, and personal characteristics that all flow into the user's intention.

Motivating USE




Environmental Enablers

*External factors in the user's environment that make technology easier or more attractive to use.*

- Performance Expectancy
  The belief that the technology will help the user do their tasks better, faster, or more efficiently.
  *Example:* "If I use this system, I can finish my work quicker."
- Effort Expectancy
  How easy the technology feels to use. If it is simple, intuitive, and does not require much training, users develop a positive intention.
  *Example:* "This tool is easy to learn, so I'm happy to start using it."
- Facilitating Conditions
  The degree to which an organization or environment provides support—such as training, help desks, good infrastructure, and technical resources.
  *Example:* "I know IT support is available if I need help."
- Peer Influence (Social Influence)
  The pressure, encouragement, or expectations from colleagues, supervisors, or friends.
  *Example:* "Everyone on my team is using this system, so I should too."

In short: Environmental enablers are the *context* around the user. They are external, social, and organizational factors that create the conditions that *allow* and *encourage* technology use.

Psychological Factors

*Internal motivations and personal feelings that influence whether a user wants to adopt or continue using a technology.*

- Hedonic Motivation
  The enjoyment, fun, or positive emotional experience from using the technology.
  *Example:* "I actually like using this app—it feels satisfying."
- Learning Value
  The feeling that using the technology helps the user grow, develop skills, or gain new knowledge.
  *Example:* "Using this tool helps me learn new things, so it's worth the effort."
- Habit
  The extent to which using the technology has become automatic. When something becomes a habit, people continue using it without thinking.
  *Example:* "I open this app automatically every morning."

In short: Psychological factors are *inside the user*: emotions, enjoyment, personal growth, and behavioral patterns. They drive *internal motivation* to use technology

# THEORIES COMBINED

| | Innovators | Early adopters | Early Majority | Late Majority | Laggards |
|---|---|---|---|---|---|
| Performace expectancy | High | High | Medium | Medium | Low |
| Effort expectancy | Low | Medium | Medium | High | High |
| Social influence | None | Low | Medium | High | None |
| Facilitating conditions | None | Low | Medium | High | High |
| Hedonic motivation | High | High | Medium | Low | None |
| Price value | High | High | Medium | Low | Low |
| Habits | None | Low | Medium | High | None |
| Intention to use | High | High | Medium | Medium | None |
| Actual use | High | High | Medium | Medium | Low |

- It shows how motivation changes across adopter groups.
- It connects Diffusion Theory (adopter categories) with UTAUT2 motivators, showing that:
    - *Innovators* are driven by excitement, novelty, and performance.
    - *Early Majority* need social proof and ease-of-use.
    - *Late Majority* need strong support and external pressure.
    - *Laggards* resist until there is no alternative.

In other words, different groups adopt technology for different reasons, and this table summarizes those reasons in one combined framework.

**Environmental Enablers**

These are external conditions in the user's surroundings that make technology easier to adopt and more attractive to use. They come from the environment — not from the user's internal motivation.

- Job performance outcome expectancy (Performance Expectancy)
    - How strongly the user believes the technology will improve their job performance, productivity, or effectiveness.
      If people expect clear, concrete benefits, their intention to use increases.
- Ease of use / ability to master (Effort Expectancy)
    - How easy the technology feels to learn and operate.
      If it is intuitive, simple, and does not require much training, users are more willing to use it.
- Organizational infrastructural support (Facilitating Conditions)
    - The extent to which the organization provides tools, training, technical assistance, and resources needed to use the system.
      Good support structures remove barriers to use.
- Influence of peers (Social Influence)
    - The degree to which colleagues, managers, or social groups encourage or expect the user to adopt the technology.
      Seeing others use a technology increases pressure and motivation to adopt.

## GENERATIONAL DIFFERENCES

| Environmental enablers | Generation Z | Millennials | Generation X |
|---|---|---|---|
| Performance Expectancy | Augmentation and enhancement | Job assistance | Improved job benefits and performance |
| Effort Expectancy | Instant intuitiveness | Work behavior adjustments | Disruptive to workflow |
| Social influence | Community of tech peers | Work peers and mass reviews | Workplace and industry norms |
| Facilitating Conditions | Digital self-service support solutions | workplace courses and training. | Tech support, direct assistance, and hands-on-training. |

**Performance Expectancy**

- *How each generation expects technology to improve their performance.*
    - **Generation Z**
        - See technology as a way to **augment and enhance** their abilities.
        - Expect tools to make them faster, smarter, and more capable.
    - **Millennials**
        - View technology mainly as **job assistance**—a tool that helps them accomplish tasks more efficiently.
        - Less focused on enhancement, more on support.
    - **Generation X**
        - Expect **improved job benefits and performance**, but only if the tool clearly fits their established workflow.
        - Need proven value before engaging.

**Effort Expectancy**

- *How easy the technology should be to use.*
    - **Generation Z**
        - Expect **instant intuitiveness**; the tool must be simple and self-explanatory.

        - They dislike manuals and long instructions.
    - **Millennials**
        - Accept that technology may require some **work behavior adjustments**.
        - More tolerant of learning curves.
    - **Generation X**
        - Often find new tools **disruptive to workflow**.
        - Prefer systems that integrate with existing routines and require minimal change.

**Social Influence**

- *How peers and social norms affect adoption.*
    - **Generation Z**
        - Influenced by a **community of tech peers**—friends, online groups, social networks.
        - Adoption spreads through peer groups quickly.
    - **Millennials**
        - Affected by **work peers and mass reviews**.
        - They trust colleagues' experiences and online ratings.
    - **Generation X**
        - Influenced by **workplace and industry norms**, not peers.
        - Prefer recommendations from management or established professionals.

**Facilitating Conditions**

- *The type of support each generation needs to adopt technology.*
    - **Generation Z**
        - Prefer **digital self-service support** such as chats, FAQs, and automated help.
        - They want independence and fast answers.
    - **Millennials**
        - Value **workplace courses and formal training**.
        - Prefer structured guidance and tutorials.
    - **Generation X**
        - Need **tech support, direct assistance, and hands-on training**.
        - Prefer personalized support over digital self-help tools.

Psychological Factors

- Intrinsic enjoyment / satisfaction expected (Hedonic Motivation)
    - This refers to the pleasure, fun, or emotional satisfaction a user expects to get from using the technology.
    - If using the system feels enjoyable, motivating, or personally rewarding, users are more likely to adopt and continue using it.
- Cost–benefit evaluation / decision calculus (Learning Value)
    - The user mentally weighs what they gain (knowledge, efficiency, skills) against what they invest (time, effort, money).
    - When the perceived learning value or personal gain is high, users feel the technology is “worth it.”
- Evaluating the ability to make the technology habitual (Habit)
    - This is the user’s belief about whether the technology can become part of their daily routine.
    - If a tool feels easy to incorporate into regular behavior, it increases long-term use and decreases resistance.

## GENERATIONAL DIFFERENCES

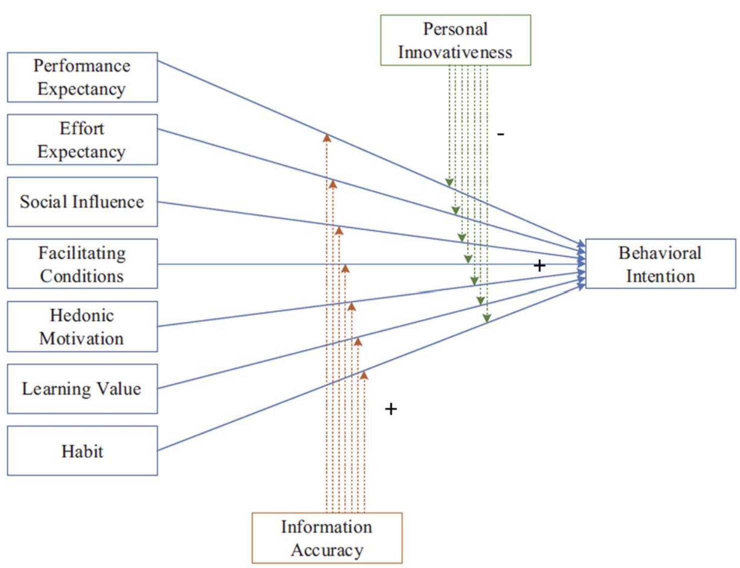
| Psychological factors | Generation Z | Millennials | Generation X |
|---|---|---|---|
| **Hedonic Motivation** | Enjoyment and flow | Work competences | Job performance |
| **Learning value** | Evaluate benefits | Positive | Evaluate costs |
| **Habits** | Self-evident | Can be taught | Hard change |
| **Information acccuracy** | Inherent trust | Conditional trust | Distrust |
| **Tech-savviness** | Tech Literate | Tech proficiency | Tech confident |

- Hedonic Motivation
    - *How each generation experiences enjoyment or satisfaction when using technology.*
        - Generation Z
            - Seek enjoyment and flow
            - Technology use should feel smooth, fun, and engaging
        - Millennials
            - Link enjoyment to work competences
            - They enjoy tech mainly when it helps them work smarter or feel skilled
        - Generation X
            - Focus on job performance
            - Tech is enjoyable only if it clearly improves results or productivity
- Learning Value
    - *How each generation evaluates what they gain from using technology.*
        - Generation Z
            - Evaluate benefits
            - They adopt tech when it gives new abilities or learning opportunities
        - Millennials
            - Generally positive toward learning new technologies
            - See tech as a tool for growth and career development
        - Generation X

            - Evaluate costs
            - Focus on how much effort or time learning will require, often weighing it against disruption
- Habits
    - *How easily each generation forms or changes habits related to technology.*
        - Generation Z
            - Tech habits are self-evident
            - They naturally integrate tech into daily routines
        - Millennials
            - Tech habits can be taught
            - They adapt but may need structured guidance
        - Generation X
            - Hard change
            - Existing routines are strong, and new tech habits require major effort
- Information Accuracy
    - *How each generation perceives the trustworthiness of digital information*.
        - Generation Z
            - Show inherent trust in digital information
            - Assume systems and platforms are accurate by default
        - Millennials
            - Have conditional trust
            - Trust accuracy only if information comes from reliable or verified sources
        - Generation X
            - Tend to distrust
            - More skeptical of digital information and require strong evidence
- Tech-savviness
    - *General ability and confidence with technology.*
        - Generation Z
            - Tech literate
            - Grew up with technology and learn new tools quickly
        - Millennials
            - Tech proficient
            - Comfortable and competent, but not "native" users
        - Generation X
            - Tech confident
            - May not have grown up with it, but often confident once trained and supported

Moderators

- **Legacy Moderators**
    - Traditional models (like early TAM and UTAUT) used **demographic and experience-based moderators**:
        - **Age**
            - Younger users adopt more easily; older users may need more support and time.
        - **Gender**
            - Historically used to capture differences in technology confidence and motivation (less relevant today).
        - **Job Experience**
            - The more experience a person has in their role or organization, the more (or less) likely they are to adopt new tools depending on comfort and habits.
    - *These moderators assume that demographic characteristics shape technology behavior.*
- **Modern Moderators**
    - Newer models use **psychological and cognitive moderators** that better explain *why* individuals differ in their adoption behavior.
        - **Personal Innovativeness**
            - *(from Diffusion Theory)*
            - Describes how willing a person is to try new technologies.
            - High innovativeness → faster adoption, higher intention to use, less resistance.
            - Low innovativeness → slower adoption, stronger need for evidence, support, and social proof.
            - *Origin:* Diffusion of Innovation theory (Rogers)
        - **Information Accuracy (Trust in Information Quality)**
            - *(from the ISS model)*
            - Measures how much users trust the **quality, correctness, and reliability** of system output.
            - High trust → higher intention and higher system use.
            - Low trust → low intention, discontinuance, or rejection.
            - *Origin:* Information Systems Success (ISS) model



The diagram combines the core predictors of technology acceptance with the two modern moderators introduced in your previous slide. The left side contains the traditional UTAUT2 predictors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, learning value, and habit. These variables all represent different reasons why a user might form a positive intention to use a technology. Each of these constructs sends a direct influence toward behavioral intention, indicating that they shape whether a user plans to adopt or continue using a system.

Into this familiar structure, the model adds two moderating forces—information accuracy and personal innovativeness—which modify the strength or direction of these relationships. Information accuracy, drawn from the ISS model, strengthens the connection between the predictors and behavioral intention. This means that when users trust the accuracy and reliability of the system's output, the positive effects of the predictors on intention become stronger. For example, if someone believes the information generated by the system is high-quality, the influence of performance expectancy or learning value on their intention becomes more pronounced. Trust in information thus amplifies the attractiveness of the technology.

Personal innovativeness, derived from diffusion theory, works in the opposite direction: it weakens or reduces the impact of environmental and psychological motivators on behavioral intention. Highly innovative individuals tend to rely less on social influence, facilitating conditions, or ease-of-use considerations because they are willing to try new technologies regardless of external support or complexity. Their adoption decision is driven more by curiosity and internal motivation than by external enablers. Therefore, the dashed green arrows show that as personal innovativeness increases, the importance of the individual predictors decreases.

Taken together, the model proposes that behavioral intention emerges not only from the standard predictors of technology acceptance but also from the user's level of trust in the accuracy of the technology and their personal tendency to experiment with new tools. Information accuracy strengthens the entire intention-formation process, while personal innovativeness partially bypasses it. The final outcome is a richer, more realistic understanding of why different types of users form different levels of intention to adopt new technologies.

## Data Collection

Quetsionare

- Matrix questions
  - Questions arranged in a table format.
  - Respondents evaluate several statements using the same scale.
  - Efficient way to measure multiple related items.
- Measurement with Likert Scale
  - Respondents rate agreement (e.g., 1 = strongly disagree → 5 = strongly agree).
  - Used to measure attitudes, perceptions, and intentions.
  - Each construct (e.g., performance expectancy) is measured with several Likert items.
- When You Have a Large Sample (large n)
  - Factor analysis on measurement questions
    - Used to identify which items belong together.
    - Helps confirm that the questions correctly measure each construct (e.g., performance expectancy).
    - Reduces many items into fewer "factors."
  - Reliability = Cronbach's Alpha on factors
    - Tests internal consistency of items that form one factor.
    - High alpha (≥0.7) means the items all measure the same underlying concept well.
- When You Have a Small Sample (small n)
  - Use averages on questions
    - You simply average the Likert responses of each item belonging to the same construct.
    - No factor analysis (sample too small).
    - No reliability testing (Cronbach's Alpha unstable with small samples).

Always include

**Table 2.** Profile of respondents.

| Demographic Factors | Categories | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Female | 218 | 53.7 |
| | Male | 188 | 46.3 |
| Age | 18–21 | 181 | 44.6 |
| | 22–25 | 103 | 25.4 |
| | 26–30 | 74 | 18.2 |
| | Above 30 | 48 | 11.8 |
| Race | Malay | 217 | 53.4 |
| | Chinese | 92 | 22.7 |
| | Indian | 59 | 14.5 |
| | Others | 38 | 9.4 |
| Academic Level | Bachelor student | 279 | 68.7 |
| | Master student | 127 | 31.3 |

This table provides a demographic profile of the respondents who participated in a questionnaire or survey. Its purpose is to show who the participants are, so readers can judge how representative and balanced the sample is.

The table lists key demographic factors—such as gender, age, race, and academic level—and shows, for each category, the number of respondents and the percentage they represent in the total sample.

In research, this type of table is always included to:

- Describe the sample population
- Show diversity or imbalance in characteristics
- Help assess the validity and generalizability of the findings
- Allow comparison with other studies or populations
- Reveal potential biases (e.g., too many young respondents)

Overall, this table helps readers understand who participated, which is essential for interpreting the results of the study.

| Items | Source |
|---|---|
| Performance expectancy | Abdullah et al. (2016) |
| Using ChatGPT would allow me to accomplish learning tasks more quickly. | |
| Using ChatGPT would improve my learning performance. | |
| Using ChatGPT would increase my productivity in learning. | |
| Using ChatGPT would enhance my effectiveness in learning. | |
| Using ChatGPT would make learning easier. | |
| I find ChatGPT useful in my learning. | |
| Effort expectancy | Nikolopoulou et al. (2021) |
| Learning how to use ChatGPT is easy for me. | |
| My interaction with ChatGPT is clear and simple. | |
| I find ChatGPT easy to use for my learning. | |
| It is easy for me to become skilful at using ChatGPT. | |
| Social influence | Rudhumbu (2022) |
| People who are important to me think I should use ChatGPT in my studies. | |
| People who influence my behaviour think I should use ChatGPT for my studies. | |
| People whose opinions I value prefer I should use ChatGPT for my studies. | |
| Facilitating conditions | Rudhumbu (2022) |
| I have the resources I need to use ChatGPT for my studies. | |
| I have the knowledge necessary to use ChatGPT for my studies. | |
| ChatGPT is compatible with other ICT tools I use in my studies. | |
| I can get help from others when I face difficulties learning using ChatGPT. | |
| Hedonic motivation | Nikolopoulou et al. (2021) |
| Using ChatGPT in my studies is fun. | |
| Using ChatGPT in my studies is enjoyable. | |
| Using ChatGPT in my studies is very entertaining. | |
| Learning value | Sitar-Taut and Mican (2021) |
| Using ChatGPT increases my knowledge and helps me to be successful in my studies. | |
| ChatGPT is a very effective educational tool and helps me to improve my learning process. | |
| ChatGPT saves my time in searching for materials. | |
| ChatGPT helps me to achieve my learning goals. | |
| Habit | Farooq et al. (2017) |
| I often use chatbots. | |
| I am used to using chatbots. | |
| The use of chatbots is a habit for me. | |
| Personal innovativeness | Nikou and Economides (2017) |
| I like to experiment with new information technology | |
| If I heard about a new information technology, I would look for ways to experiment with it. | |
| I am usually the first to try out new information technology. | |
| Information accuracy | Filieri and McLeay (2014) |
| The information I obtain from ChatGPT is correct. | |
| The information I obtain from ChatGPT is accurate. | |
| The information I obtain from ChatGPT is reliable. | |
| Intention to use | Nikou and Economides (2017) |
| I indent to use ChatGPT in my studies in the future. | |
| I plan to use ChatGPT in my studies in the future. | |
| I predict I would use ChatGPT in my studies in the future. | |

Table 1. Measurement model assessment.

| Constructs | Items | Loadings | CR | AVE |
|---|---|---|---|---|
| Performance Expectancy (PE) | PE1 | 0.782 | 0.946 | 0.745 |
| | PE2 | 0.833 | | |
| | PE3 | 0.855 | | |
| | PE4 | 0.810 | | |
| | PE5 | 0.945 | | |
| | PE6 | 0.940 | | |
| Effort Expectancy (EE) | EE1 | 0.872 | 0.943 | 0.805 |
| | EE2 | 0.916 | | |
| | EE3 | 0.923 | | |
| | EE4 | 0.876 | | |
| Social Influence (SI) | SI1 | 0.874 | 0.866 | 0.683 |
| | SI2 | 0.742 | | |
| | SI3 | 0.858 | | |
| Facilitating Conditions (FC) | FC1 | 0.815 | 0.883 | 0.654 |
| | FC2 | 0.818 | | |
| | FC3 | 0.820 | | |
| | FC4 | 0.780 | | |
| Hedonic Motivation (HM) | HM1 | 0.762 | 0.852 | 0.659 |
| | HM2 | 0.923 | | |
| | HM3 | 0.738 | | |
| Learning Value (LV) | LV1 | 0.827 | 0.877 | 0.641 |
| | LV2 | 0.790 | | |
| | LV3 | 0.798 | | |
| | LV4 | 0.787 | | |
| Habit (HAB) | HAB1 | 0.815 | 0.863 | 0.680 |
| | HAB2 | 0.939 | | |
| | HAB3 | 0.702 | | |
| Personal Innovativeness (PI) | PI1 | 0.892 | 0.865 | 0.683 |
| | PI2 | 0.848 | | |
| | PI3 | 0.731 | | |
| Information Accuracy (IA) | IA1 | 0.831 | 0.839 | 0.635 |
| | IA2 | 0.764 | | |
| | IA3 | 0.794 | | |
| Intention to Use (IU) | IU1 | 0.915 | 0.947 | 0.855 |
| | IU2 | 0.926 | | |
| | IU3 | 0.934 | | |

CR: Composite Reliability; AVE: Average Variance Extracted.

**The Left Side: Questionnaire Items**

- The left side lists all the **survey statements** used to measure each construct, such as:
  - Performance Expectancy
  - Effort Expectancy
  - Social Influence
  - Facilitating Conditions
  - Hedonic Motivation
  - Learning Value
  - Habit
  - Personal Innovativeness
  - Information Accuracy
  - Intention to Use
- Each construct is measured with multiple Likert items (e.g., PE1, PE2, PE3...), which ensures reliability.
- These items come from validated sources (shown next to each block), meaning the study uses measurement scales from previous research.
- Overall:
  This side shows *what the respondents were asked* and *which items measure each theoretical variable*.
- The Right Side: Measurement Model Statistics
- The right side provides three important statistics for each construct:
  - Loadings
    - Each item (e.g., PE1, PE2...) has a factor loading, which shows how strongly that item reflects the

        - underlying construct.
        - Loadings above 0.7 are considered strong.
        - This table shows mostly high loadings, indicating good measurement quality.
        - Means: Each item properly measures what it is supposed to measure.
    - CR – Composite Reliability
        - CR shows how consistently the items measure a construct.
        - Values above 0.7 are acceptable; values above 0.9 are excellent.
        - In this table, CR values are all strong (e.g., 0.946, 0.943, 0.866…), which means the constructs have high internal reliability.
        - Means: The items for each construct work together consistently.
    - AVE – Average Variance Extracted
        - AVE shows how much of the variance in the items is explained by the construct.
        - Values above 0.5 indicate good convergent validity.
        - Here, all AVE values are above the threshold, indicating good validity.
        - Means: The construct explains most of the variance in its items.
- What This Table Means Overall
    - This table demonstrates that:
        - The questionnaire items are statistically sound
            - (all high factor loadings)
        - The constructs are measured reliably
            - (high composite reliability)
        - The constructs have strong convergent validity
            - (AVE > 0.50)
        - The measurement model is solid
            - and appropriate for use in structural equation modeling or regression analysis.
            - In short, the measurement model passes all required statistical checks, meaning the results of the study can be trusted because the constructs were measured properly.

Analyzing

# SYMMETRIC, DIRECT, HYPOTHESIS TESTING

**Table 4.** Results of hypotheses testing.

| Hypotheses | Relationships | Path Coefficients | *T* Values | *p* Values | Decision |
|---|---|---|---|---|---|
| Main Model | | | | | |
| H1 | PE → IU | 0.207 | 3.625 | 0.000*** | Supported |
| H2 | EE → IU | 0.132 | 1.951 | 0.048* | Supported |
| H3 | SI → IU | 0.056 | 1.077 | 0.0282 | Not Supported |
| H4 | FC → IU | 0.075 | 1.266 | 0.206 | Not Supported |
| H5 | HM → IU | 0.151 | 2.351 | 0.019* | Supported |
| H6 | LV → IU | 0.175 | 2.259 | 0.024* | Supported |
| H7 | HAB → IU | 0.045 | 1.005 | 0.315 | Not Supported |
| Moderating Effect of Personal Innovativeness | | | | | |
| H8a | PI*PE → IU | −0.069 | 2.201 | 0.028* | Supported |
| H8b | PI*EE → IU | −0.071 | 2.250 | 0.025* | Supported |
| H8c | PI*SI → IU | −0.065 | 1.709 | 0.046* | Supported |
| H8d | PI*FC → IU | −0.077 | 2.167 | 0.031* | Supported |
| H8e | PI*HM → IU | −0.041 | 1.362 | 0.174 | Not Supported |
| H8f | PI*LV → IU | 0.001 | 0.034 | 0.973 | Not Supported |
| H8g | PI*HAB → IU | −0.076 | 1.645 | 0.101 | Not Supported |
| Moderating Effect of Information Accuracy | | | | | |
| H9a | IA*PE → IU | −0.010 | 0.216 | 0.829 | Not Supported |
| H9b | IA*EE → IU | −0.023 | 0.454 | 0.650 | Not Supported |
| H9c | IA*SI → IU | −0.106 | 2.153 | 0.032* | Not Supported |
| H9d | IA*FC → IU | −0.034 | 0.812 | 0.417 | Not Supported |
| H9e | IA*HM → IU | −0.027 | 0.677 | 0.499 | Not Supported |
| H9f | IA*LV → IU | 0.077 | 1.464 | 0.143 | Not Supported |
| H9g | IA*HAB → IU | −0.005 | 0.092 | 0.927 | Not Supported |

$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

**1. MAIN MODEL (Direct Effects on Intention to Use)**

This part tests whether each predictor directly increases Intention to Use (IU).

⭐ **Rule:**

- If **p < 0.05** → the effect **IS significant** → **hypothesis supported**
- If **p > 0.05** → the effect **IS NOT significant** → **hypothesis not supported**

---

**H1: PE → IU (Supported)**

- **p = 0.000 < 0.001 → significant**
- Meaning: Performance Expectancy **positively affects** intention.
- If people think ChatGPT improves performance, they intend to use it.

✓ **Exam sentence:**

"H1 is supported because p < 0.001; performance expectancy significantly increases intention to use."

---

**H2: EE → IU (Supported)**

- **p = 0.048 < 0.05 → significant**
- Meaning: Ease of use increases intention.
- Users are more likely to use ChatGPT when it feels easy.

✓ **Exam sentence:**

"H2 is supported (p < 0.05), showing that effort expectancy significantly affects intention."

---

**H3: SI → IU (Not Supported)**

- **p = 0.282 > 0.05 → NOT significant**
- Meaning: Social Influence does **not** shape intention.
- Students don't use ChatGPT because of others.

✓ **Exam sentence:**

"H3 is not supported because p > 0.05; social influence does not affect intention to use."

---

**H4: FC → IU (Not Supported)**

- **$p = 0.206 > 0.05$ → NOT significant**
- Meaning: No effect of facilitating conditions.
- Support, training, or resources don't matter.

✓ Exam sentence:

"H4 not supported ($p > 0.05$). Facilitating conditions do not predict intention."

---

**H5: HM → IU (Supported)**

- **$p = 0.019 < 0.05$ → significant**
- Meaning: Fun/enjoyment increases intention.

✓ Exam sentence:

"H5 supported ($p < 0.05$). Hedonic motivation significantly affects intention."

---

**H6: LV → IU (Supported)**

- **$p = 0.024 < 0.05$ → significant**
- Meaning: Learning value increases intention.

✓ Exam sentence:

"H6 supported ($p < 0.05$). Learning value positively influences intention."

---

**H7: HAB → IU (Not Supported)**

- **$p = 0.315 > 0.05$ → NOT significant**
- Meaning: Habit does not influence intention.
- ChatGPT is still too new for strong habits.

✓ Exam sentence:

"H7 not supported ($p > 0.05$). Habit does not significantly influence intention."

---

⭐ **Summary of Main Model for Exam**

Significant predictors (supported, $p < 0.05$):

✓ Performance Expectancy

✓ Effort Expectancy

✓ Hedonic Motivation

✓ Learning Value

Non-significant predictors (not supported, $p > 0.05$):

✗ Social Influence

✗ Facilitating Conditions

✗ Habit

---

**2. Moderating Effect of PERSONAL INNOVATIVENESS (PI)**

Moderator means: **Does PI change the strength of the relationship?**

⭐ **Interpretation rule:**

- **Significant p-value ($p < 0.05$)** → moderation effect exists
- **Negative coefficient** → PI *weakens* the relationship
- **Positive coefficient** → PI strengthens the relationship

---

**H8a: PI × PE → IU (Supported)**

- **$p = 0.028 < 0.05$ → significant**
- **Coefficient = -0.069 → negative**

  ➡️ High-inventive users rely LESS on performance expectancy.

---

**H8b: PI × EE → IU (Supported)**

- **$p = 0.025 < 0.05$ → significant**
- **Coefficient = -0.071 → negative**

  ➡️ High-inventive users do not depend on ease of use.

---

**H8c: PI × SI → IU (Supported)**

- **$p = 0.046 < 0.05$ → significant**
- **Coefficient = -0.065 → negative**

  ➡️ Innovators do NOT care what others think.

---

**H8d: PI × FC → IU (Supported)**

- **$p = 0.031 < 0.05$ → significant**
- **Coefficient = -0.077 → negative**

  ➡️ Innovators do not need organizational support.

---

**H8e, H8f, H8g (NOT supported)**

Hedonic Motivation, Learning Value, Habit

- All **$p > 0.05$** → not significant

  ➡️ PI does NOT change these relationships.

---

⭐ **Summary for Exam (PI Moderation)**

"Personal Innovativeness significantly moderates the effects of PE, EE, SI, and FC ($p < 0.05$), and all coefficients are negative, meaning the relationships become weaker for highly innovative users. PI does not moderate hedonic motivation, learning value, or habit ($p > 0.05$)."

---

**3. Moderating Effect of INFORMATION ACCURACY (IA)**

⭐ **Only ONE supported moderation:**

**H9c: IA × SI → IU (Supported)**

- **$p = 0.032 < 0.05$ → significant**
- **Coefficient = -0.106 (negative)**

  ➡️ When trust in information is high, social influence matters *a little more*
  —but still in a weak/negative direction.

---

❌ **All other moderations NOT supported ($p > 0.05$):**

- IA does NOT moderate effects of PE, EE, FC, HM, LV, HAB.

➡️ Users evaluate usefulness, effort, etc. independently of accuracy beliefs.

---

⭐ **Exam Summary for IA Moderation**

"Information Accuracy only moderates the effect of Social Influence on Intention ($p < 0.05$). All other interaction effects are not significant ($p > 0.05$), indicating that trust in information does not change the influence of performance, effort, hedonic motivation, learning value, or habit."

**Final Exam Answer — Fließtext (English, Detailed)** ⭐

The results of the main structural model show that four variables—Performance Expectancy, Effort Expectancy, Hedonic Motivation, and Learning Value—have a significant and positive impact on the intention to use the technology. All four predictors show p-values below 0.05, indicating that they meaningfully increase behavioral intention. This means that students intend to use ChatGPT primarily because they believe it will improve their performance, because it is easy to use, because it is enjoyable, and because it provides clear learning benefits. In contrast, Social Influence, Facilitating Conditions, and Habit show p-values above 0.05 and therefore do not significantly predict intention. These results suggest that adoption is not driven by pressure or encouragement from others, nor by institutional support structures, nor by established routines. ChatGPT is not yet habitual behavior, and its use is largely independent of social or environmental enablers. Instead, intention is driven by individual perceptions of usefulness, ease, enjoyment, and added educational value.

The moderating analysis shows that Personal Innovativeness significantly alters several of the relationships in the main model. Specifically, the interaction terms between innovativeness and Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions all show significant p-values ($p < 0.05$), and all coefficients are negative. This means that for individuals who are highly innovative and willing to experiment with new technologies, the strength of these predictors becomes weaker. Highly innovative users do not depend strongly on performance benefits, ease of use, peer influence, or institutional support when forming their intention to use the technology. They adopt because they are intrinsically motivated to try new tools, not because external factors push or pull them. In contrast, Personal Innovativeness does not moderate the effects of Hedonic Motivation, Learning Value, or Habit ($p > 0.05$). These constructs remain equally important or unimportant regardless of whether a user is highly innovative or not, which makes sense because enjoyment, perceived learning benefit, and habitual tendencies are internal psychological processes rather than effects that vary with innovativeness.

The moderating effect of Information Accuracy shows a very different pattern. Information Accuracy, which represents the user's trust in the correctness and reliability of ChatGPT's output, moderates only one relationship: the effect of Social Influence on Intention to Use. This interaction is significant ($p < 0.05$), indicating that when users trust the accuracy of the information produced by the system, the influence of peers or important others becomes slightly more relevant. In other words, social recommendations matter only when users believe the system is accurate. All other moderation effects involving Information Accuracy show p-values greater than 0.05, which means that trust in information does not meaningfully alter the effects of performance, effort, facilitating conditions, enjoyment, learning value, or habit on intention. These relationships remain stable regardless of whether accuracy is perceived as high or low.

Taken together, the results demonstrate that behavioral intention is primarily shaped by personal and psychological assessments of the technology, not by social or institutional factors. Personal Innovativeness weakens reliance on traditional predictors, while Information Accuracy plays only a limited moderating role. Overall, the model highlights that adoption of AI-based learning tools is highly individual and benefit-driven, with trust and innovativeness shaping how different users respond to the technology.

General approach:

**HE UNIVERSAL APPROACH (WORKS FOR ANY MODEL)** ⭐

**Step 1: Identify which hypotheses are supported**

Use the rule:

- **$p < 0.05$ → significant → supported**
- **$p > 0.05$ → not significant → not supported**

✓ Do this *before* interpreting anything.

---

**Step 2: Interpret each supported path**

For each significant result, say:

**"Variable A has a significant positive/negative effect on Variable B ($p < 0.05$). This means that when A increases, B also increases/decreases."**

It does NOT matter what the variables are.

This sentence structure works for every model.

Example:

"Performance Expectancy has a significant positive effect on Intention to Use ($p < 0.001$), meaning that higher perceived usefulness increases intention."

---

**Step 3: Interpret each non-supported path**

Use the universal sentence:

**"The effect of A on B is not significant ($p > 0.05$). This means A does not meaningfully predict B in this sample."**

Again, this works for ANY model.

---

**Step 4: Interpret moderation (always same logic)**

Moderation ALWAYS follows this rule:

⭐ **Supported moderation ($p < 0.05$):**

**"Variable M changes the strength of the relationship between X and Y."**

If coefficient is negative:

"High levels of M weaken the relationship."

If positive:

"High levels of M strengthen the relationship."

⭐ **Non-supported moderation ($p > 0.05$):**

**"Variable M does not moderate the relationship between X and Y."**

This ALWAYS works.

---

**Step 5: Provide an overall summary**

A general summary sentence ALWAYS works:

**"Overall, the model shows that intention is driven mainly by significant personal predictors, while non-significant predictors do not influence intention. Moderation results indicate that some relationships vary by moderator, while others remain stable."**

That's it. Universal.

# HYPOTHESES RESULTS

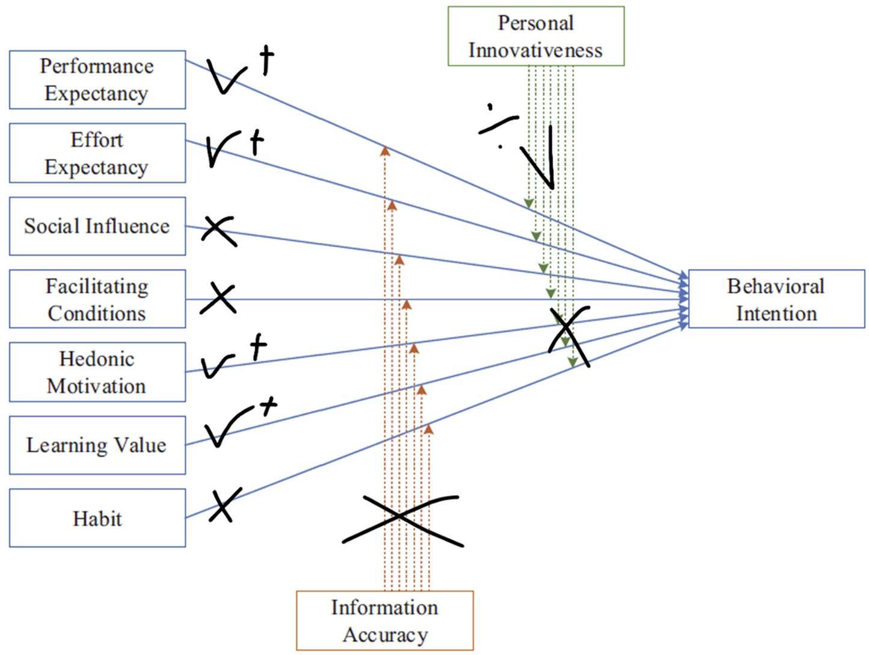



Figure 1. Research model.

This slide summarizes which hypotheses in the research model were supported and which were not. The arrows with checkmarks (✓) show significant effects, while the X marks show non-significant effects.

**1. Direct Effects (Main Model)**

The model examines how different predictors affect **Behavioral Intention**.

Four predictors have a **significant positive effect** (✓):

- **Performance Expectancy** (believing ChatGPT will help performance)
- **Effort Expectancy** (ease of use)
- **Hedonic Motivation** (fun/enjoyment)
- **Learning Value** (learning benefits)

These factors all have **$p < 0.05$**, meaning they significantly increase the intention to use the technology.

Three predictors are **not significant** (X):

- **Social Influence**
- **Facilitating Conditions**
- **Habit**

These have **$p > 0.05$**, meaning they do **not** meaningfully impact intention in this study.

This means students decide based on personal usefulness, ease, and enjoyment rather than social pressure, organizational support, or habit.

**2. Moderation by Personal Innovativeness**

Personal Innovativeness (PI) shows **several significant moderating effects**.

The green arrows represent PI *moderating* (changing) certain relationships.

The slide shows:

- PI significantly moderates **Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions** (✓)
- PI does **not** moderate **Hedonic Motivation, Learning Value, or Habit** (X)

All significant moderations have **negative coefficients**, meaning:

**The more innovative a person is, the weaker the effect of these predictors becomes.**

Innovative users adopt technology because they enjoy experimenting — they don't need strong usefulness or ease-of-use perceptions to motivate them.

**3. Moderation by Information Accuracy**

Information Accuracy (IA) is represented by the orange arrows.
The big black X across IA shows:
**Information Accuracy does not significantly moderate any of the relationships.**
This means whether students trust the accuracy of ChatGPT or not does **not** change the strength of any predictor on Behavioral Intention.
All IA moderation paths had **p > 0.05**.

# ASYMMETTRIC, CONFIGURATION ANALYSIS

| Configurations | Raw coverage | Unique coverage | Consistency |
|---|---|---|---|
| Configurations for IU | | | |
| BI= *f (PE, EE, SI, FC, HM, LV, HAB, PI, IA)* | | | |
| M1: SI*PE*PI*EE*LV*IA*HM*FC | 0.595 | 0.024 | 0.977 |
| M2: SI*PE*PI*EE*LV*HM*HAB*FC | 0.571 | 0.010 | 0.979 |
| M3: SI*PE*EE*LV*IA*HM*HAB*FC | 0.575 | 0.010 | 0.975 |
| M4: SI*PI*EE*LV*IA*HM*HAB*FC | 0.576 | 0.013 | 0.978 |
| M5: PE*PI*EE*LV*IA*HM*HAB*FC | 0.580 | 0.017 | 0.980 |
| M6: ∼SI*PE*∼PI*∼EE*∼LV*∼IA*∼HM*∼HAB*∼FC | 0.471 | 0.017 | 0.928 |
| M7: ∼SI*∼PE*PI*∼EE*∼LV*∼IA*∼HM*∼HAB*∼FC | 0.473 | 0.018 | 0.945 |
| M8: ∼SI*PE*PI*∼EE*LV*∼IA*HM*∼HAB*∼FC | 0.444 | 0.006 | 0.980 |
| Solution coverage: 0.750 | | | |
| Solution consistency: 0.909 | | | |

PE: performance expectancy; EE: effort expectancy; SI: social influence; FC: facilitating condition; HM: hedonic value; LV: learning value; HAB: habit; PI: personal innovativeness; IA: information accuracy; IU: intention to use.

Unlike regression or SEM, which test **single-variable effects**, fsQCA identifies **combinations of conditions** that *together* lead to the outcome — in this case, **Behavioral Intention (IU)**.
Instead of asking *“Which variable predicts intention?”*, fsQCA asks:
**“Which combinations of variables are sufficient to produce high intention?”**
Each row (M1, M2, M3, etc.) represents a **configuration** — a *recipe* of conditions that jointly produce the outcome.

**1. Understanding the Configurations (M1–M8)**

- Each configuration is a **set of present conditions (*)** or **absent conditions (~)** that lead to **high Behavioral Intention (IU)**.
- Examples:
    - **M1:**
        - SI*PE*PI*EE*LV*IA*HM*FC
          This means:
        - High Social Influence + high Performance Expectancy + high Personal Innovativeness + high Effort Expectancy + high Learning Value + high Information Accuracy + high Hedonic Motivation + high Facilitating Conditions
          → **together produce high Intention to Use.**
        - This is a “full configuration” where *everything is high*.
    - **M6:**
        - ~SI*PE*~PI*~EE*~LV*~IA*~HM*~HAB*~FC
        - This means:
        - Low Social Influence + high Performance Expectancy + low Innovativeness + low Effort Expectancy + low Learning Value + low Accuracy + low Hedonic Motivation + low Habit + low Facilitating Conditions
          → **can still produce high Intention to Use.**
        - This shows the **asymmetry**:
          Even with many negative conditions, *one strong condition (PE)* may still lead to high IU.
        - **Key Point:**

- **Different combinations can lead to the same outcome.**
  This is the central idea of fsQCA:
- There is *no single best path* to adoption — multiple recipes work.

**2. Raw Coverage**

- Raw Coverage tells us:
- **How much of the outcome (Intention to Use) is explained by this configuration?**
- Example:
  - M1 raw coverage = **0.595**
    → M1 explains **59.5%** of high-intention cases.
- Higher raw coverage = more influential configuration.

**3. Unique Coverage**

- Unique Coverage shows:
- **How much of the outcome is explained *only* by that configuration and by no other configuration.**
- These numbers are small (0.01–0.02), meaning:
  - The solutions overlap — many recipes explain the same cases
  - This is normal in fsQCA
  - fsQCA is about *multiple sufficient paths*

**4. Consistency**

- Consistency measures:
- **How reliably this configuration leads to high Intention.**
- Consistency close to **1.00** means:
  - Whenever this combination appears,
  - The outcome also appears
- Your consistency values (0.94–0.98) are **excellent** → these combinations are valid and strong.

**5. Solution Coverage & Solution Consistency**

- **Solution coverage (0.750):**
  - The entire set of configurations explains **75%** of all cases of high intention.
- **Solution consistency (0.909):**
  - The solution reliably predicts intention in **90.9%** of cases.
  - These are very strong values → the fsQCA solution is robust.

Consistency and Coverage

Consistency

- Meaning:
  Consistency in fsQCA tells us how reliably a combination of conditions (a configuration) leads to the outcome.
- You can think of it as the fsQCA equivalent of a p-value:
  - High consistency → the configuration is a *valid, sufficient* cause of the outcome
  - Low consistency → the configuration does NOT reliably produce the outcome
- Rule of thumb (important for exam):
  - A configuration is considered *sufficient* when consistency > 0.80.
- This means:
  - If consistency = 0.90 → whenever this combination appears, the outcome appears
  - If consistency = 0.60 → this combination is not reliable → not a sufficient cause

Coverage

- Meaning:
  Coverage tells us how much of the outcome is explained by the configuration, similar to $R^2$ in regression.
  - High coverage → the configuration explains many cases
  - Low coverage → the configuration explains only a few cases
- Two types of coverage:
  - Raw Coverage: How many cases of the outcome are covered by this configuration.
  - Unique Coverage: Part of the outcome covered *only* by this configuration.
- Rule of thumb (exam friendly):
  - Raw Coverage > 0.60 indicates strong empirical relevance.
- This means:
  - The configuration explains more than 60% of the cases of high intention
    It is an important "recipe" for the outcome

# ASYMMETTRIC, CONFIGURATION ANALYSIS

$R^2 > .6$ p-value > .8 = sufficient

| Configurations | Raw coverage | Unique coverage | Consistency |
|---|---|---|---|
| Configurations for IU | | | |
| BI= *f (PE, EE, SI, FC, HM, LV, HAB, PI, IA)* | | | |
| ÷HAB M1: SI*PE*PI*EE*LV*IA*HM*FC | 0.595 | 0.024 | 0.977 |
| ÷IA M2: SI*PE*PI*EE*LV*HM*HAB*FC | 0.571 | 0.010 | 0.979 |
| ÷PI M3: SI*PE*EE*LV*IA*HM*HAB*FC | 0.575 | 0.010 | 0.975 |
| ÷PE M4: SI*PI*EE*LV*IA*HM*HAB*FC | 0.576 | 0.013 | 0.978 |
| ÷SI M5: PE*PI*EE*LV*IA*HM*HAB*FC | 0.580 | 0.017 | 0.980 |
| M6: ~SI*PE*~PI*~EE*~LV*~IA*~HM*~HAB*~FC | 0.471 | 0.017 | 0.928 |
| M7: ~SI*~PE*PI*~EE*~LV*~IA*~HM*~HAB*~FC | 0.473 | 0.018 | 0.945 |
| M8: ~SI*PE*PI*~EE*LV*~IA*HM*~HAB*~FC | 0.444 | 0.006 | 0.980 |
| Solution coverage: 0.750 | | | |
| Solution consistency: 0.909 | | | |

PE: performance expectancy; EE: effort expectancy; SI: social influence; FC: facilitating condition; HM: hedonic value; LV: learning value; HAB: habit; PI: personal innovativeness; IA: information accuracy; IU: intention to use.

What are these numbers telling?

- RAW COVERAGE (What % of high-intention people this recipe explains)
  - Raw coverage = how many people match this recipe.
  - Example:
    M1 raw coverage = 0.595
  - 💬 Meaning:
  - 59.5% of all people with high intention fit this recipe.
  - So M1 is a "big recipe" that explains many cases.
- UNIQUE COVERAGE (What % ONLY this recipe explains)

- Unique coverage = how many people ONLY this recipe explains (no overlap with others).
- Example:
  M1 unique coverage = 0.024
- 💭 Meaning:
- Only 2.4% of cases are explained uniquely by M1.
  The rest are also explained by another recipe (M2, M3, M4...).
- This is normal.
  fsQCA recipes overlap like pizza toppings — many combinations include the same ingredients.

- CONSISTENCY (How reliable the recipe is)
  - Consistency = does this recipe *always* lead to high intention?
  - Rule:
    ✓ Above 0.80 = good (sufficient)
    ✓ Above 0.90 = excellent
  - Example:
    M1 consistency = 0.977
  - 💭 Meaning:
  - 97.7% of the time this recipe leads to high intention.
    This is extremely reliable.
  - All your configurations have 0.94–0.98 → meaning:
  - ⭐ ALL these recipes reliably produce high intention

How to Read a Configuration

- Symbols:
  - PE = condition is HIGH
  - ~PE = condition is LOW
- Example:
  - SI*PE*PI means:
  - Social Influence = high
  - Performance Expectancy = high
  - Personal Innovativeness = high
  - All three combine → high Intention
- Another example:
  - ~SI * PE * ~PI means:
  - Social Influence = low
  - Performance Expectancy = high
  - Personal Innovativeness = low
  - This different combination also → high Intention
- fsQCA says:
  - There is NOT one single path to high intention —
    there are many possible combinations / recipes.

Understanding EACH Recipe (M1–M8)

- M1
  - Recipe:
    - SI*PE*PI*EE*LV*IA*HM*FC
      → Almost ALL conditions are high.
  - Raw coverage: 0.595
    - → 59.5% of all high-intention users fit this recipe.
      (VERY common recipe)
  - Unique coverage: 0.024

        - → 2.4% of users are explained ONLY by this recipe.
          (The rest overlap with other recipes.)
    - Consistency: 0.977
        - → 97.7% of people with this combination have high intention.
          (Very reliable recipe.)
    - Meaning:
    - When usefulness, ease of use, enjoyment, innovativeness, support, AND social influence are high → intention to use is very high.
- M2
    - Recipe:
        - SIPEPIEELVHMHAB*FC
          → Same as M1 but without IA.
    - Raw coverage: 0.571
        - → 57.1% of high-intention users follow this recipe.
    - Unique coverage: 0.010
        - → Only 1% are explained only by M2.
    - Consistency: 0.979
        - → 97.9% reliability.
    - Meaning:
        - High usefulness + ease + enjoyment + innovativeness + social influence → high intention, even WITHOUT accuracy.
- M3
    - Recipe:
        - SIPEEELV~IAHMHAB*FC
          → Accuracy low (~IA), everything else high.
    - Raw coverage: 0.575
        - → 57.5% of high-intention users.
    - Unique coverage: 0.010
        - → Only 1% uniquely explained.
    - Consistency: 0.975
        - → 97.5% reliability.
    - Meaning:
        - People don't need accuracy to have high intention — other benefits compensate.
- M4
    - Recipe:
        - SIPIEELV~IAHMHAB*FC
          → Social influence high, accuracy low, other things high.
    - Raw coverage: 0.576
        - → 57.6% of users.
    - Unique coverage: 0.013
        - Consistency: 0.978
    - Meaning:
        - High ease + learning value + enjoyment + innovativeness → enough for high intention even if AI output is not accurate.

- M5
    - Recipe:
        - PEPIEELVIAHMHAB*FC
          → All conditions high except social influence.
    - Raw coverage: 0.580

        - → Explains 58% of users.
    - Unique coverage: 0.017
        - Consistency: 0.980
    - Meaning:
        - People don't need social pressure to adopt the technology.
          If performance, ease, learning value, accuracy and enjoyment are high → they adopt.

THESE NEXT MODELS ARE "MINIMAL" RECIPES
ONLY 1–2 conditions are high and STILL produce high intention.
This proves multiple different paths lead to high intention.

- M6
    - Recipe:
        - ~SIPE~PI~EE~LV~IA~HM~HAB~FC
          → EVERYTHING is low except Performance Expectancy (PE).
    - Raw coverage: 0.471
        - → Explains 47.1% of users.
    - Unique coverage: 0.017
        - Consistency: 0.928
    - Meaning:
        - If people think the technology is useful, they adopt it even if:
            - ease is low
            - enjoyment is low
            - accuracy is low
            - support is low
            - habit is low
            - innovativeness is low
    - Usefulness alone can drive adoption.
- M7
    - Recipe:
        - ~SI~PEPI~EE~LV~IA~HM~HAB~FC
          → ONLY Personal Innovativeness is high.
    - Raw coverage: 0.473
    - Unique coverage: 0.018
    - Consistency: 0.945
    - Meaning:
        - Innovative people adopt even if:
        - usefulness is low
        - ease is low
        - accuracy is low
        - benefits are low
        - Innovators adopt because they love new tech.
- M8
    - Recipe:
        - ~SIPEPI~EELV~IAHM~HAB~FC
          → A mix: usefulness + innovativeness + learning + enjoyment.
    - Raw coverage: 0.444
        - → Explains 44.4% of users.
    - Unique coverage: 0.006
    - Consistency: 0.980
        - → Very reliable.

- Meaning:
    - This is a “mixed” path:
      High usefulness + high enjoyment + learning value + innovativeness lead to adoption — even if support, accuracy, habit, ease are low.

- SOLUTION COVERAGE (0.750)
  - → All recipes together explain 75% of all high-intention cases.
  - This is the fsQCA equivalent of $R^2 = 0.75$
  - (very strong model)
- SOLUTION CONSISTENCY (0.909)
  - → The whole model reliably predicts intention in 90.9% of cases.

Detailled Summary

The asymmetric configuration analysis shows that technology adoption is not driven by a single factor, but instead by multiple different combinations of conditions (called “recipes”) that can each independently lead to a high intention to use the system. In total, the analysis identifies eight sufficient configurations (M1–M8) that can produce a high level of behavioral intention (IU). Each configuration is considered sufficient because its consistency value is above 0.80, indicating that in the vast majority of cases where the combination occurs, high intention follows. The coverage values indicate how much empirical relevance each recipe has, meaning how many cases of high intention are explained by that specific combination.

The first five configurations (M1–M5) represent complex, rich recipes where most or all predictors are present with high intensity. For example, M1 shows that when performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, learning value, personal innovativeness, and information accuracy are all high, then the intention to use is extremely likely, with a consistency of 0.977. The raw coverage of 0.595 means that almost 60% of all users with high intention fit this pattern, making it one of the most empirically relevant paths. The unique coverage of 0.024 indicates that only a small portion of cases are explained exclusively by this recipe — which is normal, because many of the recipes overlap.

Similarly, M2–M5 demonstrate that slightly different combinations of high conditions can also produce high intention, even when some conditions are absent. For instance, M3 and M4 show that users still reach high intention even when information accuracy is low (~IA), meaning that good information quality is not essential for adoption as long as other benefits — such as enjoyment, ease of use, performance, and learning value — remain high. M5 shows that high intention can occur even without social influence, which indicates that users can adopt the system independently of peer pressure if the functional benefits are convincing enough.

In contrast, configurations M6–M8 represent minimalist, simplified paths to high intention. These show that even a single strong condition can be sufficient to drive intention when all other factors are low. For example, M6 demonstrates that performance expectancy alone can be enough for adoption, even if effort expectancy, social influence, innovativeness, habit, enjoyment, learning value, and information accuracy are all low. With a consistency of 0.928, this path is still highly reliable, although its raw coverage of 0.471 indicates that it explains fewer cases than the richer recipes. M7 reveals that for highly innovative individuals, personal innovativeness alone can trigger intention, regardless of low usefulness, low ease of use, low enjoyment, or low accuracy. Finally, M8 presents a mixed configuration where users adopt the system when usefulness, learning value, enjoyment, and innovativeness are high — even if ease of use, support, accuracy, and habit are low.

Overall, the solution coverage of 0.750 means that the entire set of recipes together explains 75% of all cases of high intention, which is a very strong result (similar to an $R^2$ of 0.75). The overall solution consistency of 0.909 confirms that the full model reliably predicts high behavioral intention. These findings illustrate that adoption behavior is asymmetric: there is no single universal cause that guarantees use. Instead, users can arrive at high intention through multiple different causal pathways, depending on which conditions matter most to them.

# CASE – USING FSQCA

**1. Calibrating Likert Scale Measurement**

Before fsQCA can be used, Likert-scale data must be **converted into fuzzy-set membership scores** (0 = non-member, 1 = full member).

- Likert items (1–5 or 1–7 scale) **cannot be used directly** in fsQCA.
- They must be **calibrated** so each respondent receives a degree of membership in a condition (e.g., 0.25, 0.67, 0.95).

**2. Confirm Theoretical Factors**

Before calibration, ensure the measurement scales are valid:

- **Factor Analysis**
  Confirms that items load onto the expected theoretical constructs
  (e.g., all PE items load onto the Performance Expectancy factor).
- **Reliability Analysis (Cronbach's Alpha)**
  Checks internal consistency of each construct.
  Typically: $\alpha \geq .7$ is acceptable.

**Only after this step can you average/prepare data for fsQCA.**

**3. Calculate Averages for Each Construct**

For each theoretical variable (PE, EE, SI, etc.):

- Calculate the **mean** of all items belonging to that construct.
- This creates **one value per construct** per respondent (e.g., average PE score).

These averages are the inputs for the calibration step.

**4. Calibrate Data in fsQCA Software**

You now transform the average scores into **fuzzy-set values** between 0 and 1.

**You must define 3 thresholds:**

**✓ Full Membership (1.0)**

- Threshold where respondents are considered **fully inside** the set.
- Usually chosen as the value at the **95th percentile**.
  ("Top 5% are full members.")

**✓ Full Non-Membership (0.0)**

- Threshold where respondents are definitely **outside** the set.
- Usually value at the **5th percentile**.
  ("Bottom 5% are non-members.")

**✓ Cross-Over Point (0.5)**

- Threshold where respondents are **neither inside nor outside**.
- Usually the **mean or median** of the construct, depending on data distribution (skewness) and Likert scale range.

➡️ These three points define the fuzzy-set curve.

**5. None / Mid / Full Thresholds**

In fsQCA software you need to enter the three thresholds:

- **0% membership (non-member)**
- **50% membership (cross-over)**
- **100% membership (full-member)**

The software will then assign fuzzy membership scores for each respondent.

**6. Use the Calibration Function in fsQCA Software**

Final step:

- Input the three thresholds.
- The software generates **new fuzzy-set variables** for each construct.
- These new variables (values between 0 and 1) are used in the fsQCA truth table and minimization procedure.

➡️ After calibration, you no longer use the raw Likert scores.

HYPOTHESES — Regression vs. fsQCA (Bullet Points)

- **REGRESSION (Net-Effects Logic)**
    - Regression tests **linear net effects** → "Does X directly increase Y?"
    - **Hypothesis example (Regression):**
        - **Hedonic Motivation positively influences Intention to Use technology A.**
    - **What this means:**
        - If enjoyment increases → intention increases.
        - Focus is on the **size and direction** of the effect.
        - Uses p-values ($p < .05$ = significant).
    - **Interpretation for design:**
        - To strengthen intention, the system should **increase enjoyment**.
        - BI design must ensure that the technology feels fun, engaging, satisfying.
        - HM is **one factor among many** → not required, just *helpful*.
- **FSQCA (Set-Theory Logic)**
    - fsQCA does **not** test linear effects — it tests **necessity** and **sufficiency**.
    - **Hypothesis example (fsQCA):**
        - **Hedonic Motivation is a necessary condition for Intention to Use technology A.**
    - **What "necessary condition" means:**
        - The outcome **cannot happen** without this condition.
        - Every case with high intention MUST also have high HM.
        - HM is part of the **minimum requirement** for success.
    - **Interpretation:**
        - To succeed with adoption, Hedonic Motivation must be **always present**.
        - BI design **must** include enjoyable, fun, engaging features.
        - HM is **not optional** → it is a *prerequisite*.

**⭐ Regression vs. fsQCA — Simple Comparison**

| Aspect | Regression | fsQCA |
|---|---|---|
| Logic | Net effects | Set-theory |
| Question | Does X increase Y? | Is X required for Y? |
| Output | Effect size + p-value | Necessary/sufficient conditions |
| HM Interpretation | Helpful predictor | Required condition |
| Design implication | Increase enjoyment to raise intention | Must include enjoyment for adoption to happen |

FSQCA

FSQCA is used to understand which conditions (or combinations of conditions) lead to high technology use.

It answers questions that regression cannot.

1. Which conditions are necessary to motivate technology use?

FSQCA tests for necessary conditions:

- A necessary condition must always be present for the outcome to occur.
- If the outcome happens → the condition is always high.
- Example: "Hedonic Motivation is necessary for Intention to Use" means:

  ✓ Every user with high intention also has high enjoyment.

  ✗ If enjoyment is missing, intention CANNOT be high.

This helps identify the minimum requirements for successful adoption.

2. Are there combinations of conditions?
FSQCA also identifies sufficient combinations (recipes):

- Multiple different combinations of conditions can lead to high usage.
- Example:
    - Recipe 1: High PE + High HM + High LV
    - Recipe 2: High PI only
    - Recipe 3: High PE only
    - Recipe 4: High EE + High HM + High FC

FSQCA shows that there is not one single path to motivate users —
different employees may require different combinations.
3. How should the conditions be implemented into the employee group?
FSQCA helps shape implementation strategy:

- If a condition is necessary, it must be implemented across ALL users.
  (e.g., Everyone needs high enjoyment or high usefulness.)
- If a combination works only for some employees, then:
  ✓ different groups require different interventions
  (e.g., innovators need fun; conservatives need ease of use and support).

This leads to a segment-based implementation strategy.
4. How is the condition moderated by personal innovativeness?
FSQCA can check whether Personal Innovativeness changes the recipes:

- High PI employees may require fewer conditions.
  (e.g., only PE or only PI is enough.)
- Low PI employees may require more conditions simultaneously.
  (e.g., must have PE + EE + HM + FC.)

This tells you which groups require more support.
5. Does this change the implementation considerations?
Yes — depending on Personal Innovativeness, your strategy changes:
For high innovative employees:

- Do not need training
- Do not need support
- Don't require social influence
- Adoption is self-driven
  ➡️ Minimal implementation effort

For low innovative employees:

- Need clear usefulness
- Need ease of use
- Need support and training
- Need positive peer influence
  ➡️ High implementation effort

Thus, FSQCA shows which groups require which conditions and helps customize the deployment strategy.

# NET EFFECTS - REGRESSION

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | ,741[a] | ,548 | ,524 | 1,31939325 |

a. Predictors: (Constant), meanLV, meanEE, meanSI, meanH, meanFC, meanPE, meanHM

**ANOVA[a]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 279,081 | 7 | 39,869 | 22,903 | <,001[b] |
| | Residual | 229,785 | 132 | 1,741 | | |
| | Total | 508,866 | 139 | | | |

a. Dependent Variable: meanUSE

b. Predictors: (Constant), meanLV, meanEE, meanSI, meanH, meanFC, meanPE, meanHM

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Tolerance | VIF |
| 1 | (Constant) | -,451 | ,548 | | -,824 | ,412 | | |
| | meanPE | -,089 | ,132 | -,070 | -,673 | ,502 | ,314 | 3,184 |
| | meanEE | ,037 | ,141 | ,024 | ,262 | ,794 | ,411 | 2,430 |
| | meanSI | ,255 | ,141 | ,156 | 1,805 | ,073 | ,456 | 2,194 |
| | meanFC | ,292 | ,146 | ,205 | 2,000 | ,048 | ,326 | 3,065 |
| | meanHM | ,590 | ,148 | ,461 | 3,996 | <,001 | ,257 | 3,889 |
| | meanH | ,152 | ,147 | ,108 | 1,030 | ,305 | ,309 | 3,240 |
| | meanLV | -,094 | ,136 | -,070 | -,691 | ,491 | ,330 | 3,032 |

a. Dependent Variable: meanUSE

**REGRESSION (NET EFFECTS) — Full Explanation**

- This regression model tests how strongly each factor (PE, EE, SI, FC, HM, LV) predicts actual use (USE).
    - In the ANOVA table:
        - Dependent Variable: meanUSE
            - This tells us the outcome the model is trying to predict is USE (actual use).
        - The predictor variables are listed in the Coefficients table
            - Under “Predictors”, the regression lists:
                - meanPE (Performance Expectancy)
                - meanEE (Effort Expectancy)
                - meanSI (Social Influence)
                - meanFC (Facilitating Conditions)
                - meanHM (Hedonic Motivation)
                - meanLV (Learning Value)
            - These are the independent variables (X variables).
        - So the model is:
            - USE = f(PE, EE, SI, FC, HM, LV)
- MODEL SUMMARY
    - R = .741
        - This is the correlation between all predictors together and USE.
          → Shows the model is strongly related to technology use.
    - $R^2$ = .548
        - The predictors explain 54.8% of the variance in USE.
          → This is a good model in social science.
    - Adjusted $R^2$ = .524
        - Corrects for number of predictors.
          → Still very strong.
          → Means the model generalizes well.
    - Std. Error = 1.319
        - Shows average prediction error.
          → Not directly important for exam writing.

- ANNOVA Tabel
    - F-value (22.903)
        - The F-value compares:
            - how much variance the model explains
              vs.
            - how much variance is unexplained (error)
        - Higher F-value = better model fit
        - Lower F-value = the model does not explain the data
        - There is no single magic number, BUT generally:
            - F > 10 → strong model
            - F between 2 and 10 → weak to moderate
            - F < 2 → very weak, likely NOT significant
        - Your F = 22.903, which is very high, meaning:
            - The model explains much more variance than random noise.
    - Significance (p-value < .001)
        - This is the most important number.
            - p < .05 → significant
            - p < .01 → highly significant
            - p < .001 → extremely significant
        - Your value:
            - p < .001
            - = less than 0.1% chance that the model works by accident.
            - This means:
                - The regression model is statistically valid
                - The predictors together significantly predict USE.
        - WHEN WOULD THE MODEL *NOT* BE SIGNIFICANT?
            - A model is NOT significant when:
                - ❌ p > .05
            - This means:
                - The predictors do NOT significantly explain the dependent variable.
                - The model might as well be noise.
                - The F-value will also be low (usually F < 2).

- COEFFICIENTS TABLE
    - Each row tests one predictor.
    - **Interpretation rule:**
        - **p < .05 → significant predictor**
        - **p > .05 → NOT significant**
    - Let's go through each variable:
        - **Performance Expectancy (PE)**
            - B = –.089
            - p = .502
            - ❌ **NOT significant** → PE does not predict USE here.
        - **Effort Expectancy (EE)**
            - B = .037
            - p = .794
            - ❌ Not significant → Ease of use does NOT influence use here.
        - **Social Influence (SI)**
            - B = .255

            - p = .073
            - **Marginal (trend) but not significant**
              → SI almost matters, but does *not reach significance* (p > .05).
        - **Facilitating Conditions (FC)**
            - B = .292
            - p = .048
            - **SIGNIFICANT**
              → Availability of tools/training/support **increases use**.
        - **Hedonic Motivation (HM)**
            - B = .590
            - p < .001
            - **VERY SIGNIFICANT**
              → Enjoyment/ fun is the **strongest predictor of actual use**.
            - This aligns with most studies: HM drives behavior strongly.
        - **Learning Value (LV)**
            - B = –.094
            - p = .491
            - ❌ Not significant
              → Learning benefit does **not** predict use.
- Collinearity Statistics
    - **Tolerance rule (always the same):**
        - Tolerance < **0.10** → **serious** multicollinearity
        - Tolerance < **0.20** → **potential** multicollinearity
        - Tolerance > **0.20** → **acceptable**
    - **VIF rule (always the same):**
        - VIF **1–2** → very good
        - VIF **2–5** → acceptable
        - VIF **>5** → problematic
        - VIF **>10** → serious multicollinearity and model is unreliable
- Summary
  The regression analysis examines the net effects of the different motivational factors on actual technology use. The model summary shows that the predictors together explain a substantial proportion of variance in use ($R^2$ = .548; Adjusted $R^2$ = .524), which indicates that the model has strong explanatory power. The ANOVA confirms that the overall regression model is statistically significant (F = 22.903, p < .001), meaning that the set of predictors, taken together, reliably predicts actual use behavior.
  When looking at the individual predictors, only two constructs emerge as significant drivers of use. Hedonic Motivation shows the strongest and most significant effect (B = .590, p < .001). This means that users' enjoyment, fun, and positive emotional experience with the technology are the most important determinants of actual use. In other words, people primarily engage with the system because it feels engaging and satisfying, rather than because it is useful or easy to use.
  Facilitating Conditions also significantly influence use (B = .292, p = .048). This indicates that access to support, resources, tools, and training also matters: when users perceive that the organization provides the necessary assistance, actual use increases.
  Other factors do not significantly predict actual use in this model. Performance Expectancy, Effort Expectancy, and Learning Value all have non-significant p-values (p > .05), meaning that neither perceived usefulness, ease of use, nor learning benefits directly drive use behavior in this context.
  Social Influence shows a weak trend (p = .073) but does not reach statistical significance. This means that peer pressure or recommendations from important others do not reliably translate into actual usage.

Finally, the collinearity statistics (VIF values between 2 and 4) indicate that there is no problematic multicollinearity among predictors, and thus the estimates can be interpreted with confidence.

Overall, the regression findings demonstrate that actual use of the technology is primarily driven by enjoyment (hedonic motivation) and organizational support (facilitating conditions), while the more traditional TAM factors such as usefulness and ease of use do not significantly predict behavior in this context. This highlights the importance of designing technology that is engaging and enjoyable, and ensuring that users have the necessary support in place for successful implementation.