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Open Hardware Adoption in User Innovation Communities: An Extended UTAUT2 Model

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Abstract: This study examines open hardware adoption in user innovation communities through an extended UTAUT2 model. Drawing on experiential learning and free user innovation, it adds Educational Value and Recognition Benefits to the core constructs of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. Data from 76 respondents in open hardware communities were analyzed using PLS-SEM. The initial results show that performance expectancy, effort expectancy, and educational value significantly predict behavioral intention, with performance expectancy emerging as the strongest driver. The findings suggest that practical usefulness, ease of use, and learning-related benefits for potential adopters are central to open hardware adoption, whereas reputational motivations appear less important for initial adoption. The study contributes a quantitative, theory-driven model of open hardware adoption and offers guidance for design, education, and community support.

Keywords: Open Hardware Adoption; Maker Communities; Free User Innovation; Technology Acceptance; UTAUT2

1. Introduction

Over the past three decades, the open-source paradigm has profoundly transformed how innovation is organized, governed, and diffused (Ro et al., 2024; Ghosh et al., 2002; Raymond, 1999). Originally emerging in the software domain, open-source initiatives have challenged proprietary, firm-centric innovation models by demonstrating that

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geographically distributed communities of volunteers and professionals could collectively produce complex, high-quality technological artifacts through transparent, collaborative processes (Raymond, 1999; Ghosh et al., 2002). What initially appeared as a niche ideological movement has since evolved into a feasible innovation model adopted by firms, public institutions, society and educational organizations worldwide (Zakoth et al., 2025; Tamilmani et al., 2021).

Building on the well-established success of open-source software (OSS), these principles have increasingly migrated to the physical domain through the emergence of open hardware (OH). OH refers to physical artifacts whose design files including schematics, bill of materials (BOM), mechanical drawings, and manufacturing instructions, are openly shared, enabling users to study, modify, fabricate, and redistribute tangible products (Open Source Hardware Association, OSHWA, 2020). By making hardware designs openly accessible, OH challenges traditional assumptions about intellectual property, ownership, and value capture in manufacturing-based industries (Bonvoisin & Mies, 2018; Priego and Wareham, 2023).

From innovation management perspective, OH represents more than a technological trend; it constitutes a qualitatively different mode of innovation. Rather than relying on centralized R&D departments and closed development cycles, OH projects often emerge from decentralized networks of makers, engineers, educators, researchers, and hobbyists who collaborate across organizational and national boundaries (Pearce, 2017; Li and Seering, 2019; Reinauer and Hansen, 2021). This distributed innovation logic aligns closely with broader shifts toward user innovation, open innovation, and community-based production (Von Hippel, 2005; Chesbrough, 2003), but extends them into domains historically dominated by capital-intensive manufacturing and proprietary standards. The global relevance of OH has expanded rapidly, driven by advances in digital fabrication technologies, declining costs of prototyping tools, and the growth of maker communities. Low-cost microcontrollers (e.g., Arduino), single-board computers (e.g., Raspberry Pi), and additive manufacturing technologies have dramatically lowered entry barriers to hardware innovation (Oellermann et al., 2022; Arduino, 2025). As a result, OH has become particularly prominent in contexts where traditional proprietary hardware is inaccessible, inflexible, or prohibitively expensive.

Empirical evidence highlights the societal impact of OH across multiple sectors. For example, in healthcare sector, open medical devices and diagnostic tools have been developed to address shortages and affordability challenges, particularly in developing countries (Carpentier, 2021; Pearce, 2017). In agriculture and environmental monitoring, open electronics platforms enable locally adapted sensing and automation solutions that support sustainability and resilience (Stange et al., 2023; Shukla et al., 2023). In education, OH plays a central role in hands-on STEM learning, maker-based pedagogy, and experiential education, allowing students to engage directly with the materiality of technology rather than consuming black-boxed products (Heradio et al., 2018). These developments position OH as a key enabler of inclusive social innovation, supporting customization, local production, and knowledge transfer (Stange et al., 2023; Kostakis et al., 2023). Innovation scholars increasingly recognize OH's potential to democratize technological capabilities and redistribute innovation agency beyond established firms and research institutions (Zakoth et al. 2025; Priego and Wareham, 2023; Bonvoisin, 2016). Nevertheless, despite these promises, OH adoption remains uneven, fragmented, and largely confined to specific communities and application domains.

This uneven diffusion points to a central paradox: while OH offers clear technical, economic, and educational advantages, its adoption has not yet reached the scale suggested by its potential. Recent systematic reviews confirm that, although OH initiatives continue to proliferate, sustained and widespread adoption remains limited outside niche communities and pilot projects (Reinauer & Hansen, 2021). Many OH projects struggle to move beyond early adopters, facing challenges related to usability, documentation quality, fabrication access, and long-term sustainability (Reinauer & Hansen, 2021; Bonvoisin & Mies, 2018; Allen et al., 2023). Accessibility of makerspaces and inclusive design of physical fabrication environments further conditions who can practically engage with OH projects (Allen et al., 2023).

From a theoretical standpoint, this paradox raises fundamental questions about innovation diffusion and technology acceptance related to OH adoption. Which determinants are more effective when individuals choose to adopt or not adopt OH solutions, even when they appear objectively beneficial? Which perceived benefits and barriers matter most at the individual level? In what level do social, educational, and reputational dynamics shape adoption decisions in community-driven innovation contexts?

Existing OH research has generated rich qualitative insights into governance structures, community dynamics, and design practices (Bonvoisin & Mies, 2018; Reinauer and Hansen, 2021; Shukla et al., 2023). However, the field lacks quantitative, theory-driven models capable of explaining and predicting adoption behavior across diverse user populations. As a result, practitioners and policymakers currently lack robust empirical guidance on how to design interventions that effectively accelerate OH diffusion (Zakoth et al., 2025).

1.1 Limitations of Existing Adoption Research in Open Hardware

A critical examination of the literature reveals that most empirical OH studies rely on qualitative methodologies, including case studies, interviews, ethnographies, and design narratives (Pearce, 2017; Shukla et al., 2023; Reinauer and Hansen, 2021). While these approaches are invaluable for understanding contextual richness and social meaning, they are limited in their ability to identify generalizable adoption mechanisms or compare the relative strength of competing drivers.

Moreover, quantitative adoption research in related open-source domains, most notably OSS, cannot be directly transferred to OH without careful theoretical adaptation. Hardware differs fundamentally from software in terms of materiality, production constraints, skill requirements, and infrastructure dependencies (Bonvoisin, 2016; Li and Seering, 2019; Priego and Wareham, 2023). Fabrication access, supply chains, and physical assembly introduce barriers absent in purely digital artifacts like OSS, suggesting that adoption models must explicitly account for these differences.

Recent studies explicitly call for more rigorous empirical approaches to OH adoption, emphasizing the need for validated measurement instruments and statistical modeling techniques that can capture both motivational and structural factors (Zakoth et al. 2025; Reinauer and Hansen, 2021). Addressing this gap is particularly important for innovation management research, which seeks not only to describe innovation phenomena but also to inform strategic decision-making and policy design by acknowledging the OH-specific adoption determinants.

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1.2 Positioning This Study: A Quantitative Adoption Perspective

In response to these limitations, the present study adopts a quantitative, theory-driven approach to examine individual-level adoption of OH. Specifically, we employ the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) as the core analytical framework, extending it with two constructs that are especially fitting in OH contexts: Educational Value and Recognition Benefits. UTAUT2 provides a comprehensive and empirically validated model for explaining voluntary technology adoption, integrating cognitive, affective, social, and economic determinants of behavioral intention and use (Venkatesh et al., 2012; Dwivedi et al., 2019; Tamilmani et al., 2021). Its extensive use across technology domains allows for systematic comparison and cumulative knowledge building, which is an important advantage given the current fragmentation of OH research.

Recent studies further demonstrate UTAUT2's flexibility by extending it to emerging technologies such as AI adoption in educational settings, including higher education assessment and adolescent learning contexts (Caffaratti et al., 2025; George-Reyes et al., 2025). These applications strengthens the model's suitability for analyzing emerging technology phenomena such as OH.

By applying UTAUT2 to better understand OH adoption and extending it with OH-specific constructs grounded in prior qualitative research, this study makes three interrelated contributions. First, it advances theoretical understanding of OH adoption by identifying which drivers matter most at the individual level. Second, it strengthens methodological rigor in the OH literature by introducing validated survey measures and structural equation modeling (SEM). Third, it provides actionable insights for innovators, educators, possible adopters, entrepreneurs and policymakers seeking to foster sustainable OH ecosystems.

2. Theoretical Foundations

2.1 Open hardware within free user innovation

OH projects typically arise from communities of makers and users who collaboratively develop and refine artifacts, mirroring the user innovation communities analyzed in broader work on democratizing innovation (Bonvoisin, 2017). This situates OH within a wider shift from producer dominated innovation toward user centered and community based innovation models (Von Hippel, 2005; Von Hippel, 2025).

User innovation research shows that lead users and communities often develop functionally novel products which they then freely reveal, thereby creating an intellectual commons that supports downstream commercialization and social welfare (Von Hippel, 2005, 2025). The free innovation paradigm further emphasizes that many user innovators are self rewarded (for example, by learning, enjoyment, or problem solving) and share their solutions without direct monetary compensation, a pattern that closely aligns with motivations observed in open source and OH communities (Lakhani and Wolf, 2003; Gamberdella et al., 2017). At the same time, adoption of OH remains modest in many sectors; for instance, a review of small open source wind turbines shows that diffusion depends on perceived product quality, local fabrication inputs, and the resources provided by open communities (Reinauer and Hansen, 2021).

2.2 UTAUT and UTAUT2 as adoption frameworks

The Unified Theory of Acceptance and Use of Technology (UTAUT) synthesized eight prior adoption models and identified performance expectancy, effort expectancy, social influence, and facilitating conditions as core determinants of behavioral intention and use (Venkatesh et al., 2003). UTAUT demonstrated strong explanatory power across organizational IT contexts and highlighted the moderating roles of age, gender, experience, and voluntariness of use (Venkatesh et al., 2003). Building on this foundation, UTAUT2 extended the model to consumer settings by incorporating hedonic motivation, price value, and habit, which substantially increased the variance explained in both behavioral intention and use behavior (Venkatesh et al., 2012).

Subsequent meta analytic and theoretical work has re examined UTAUT relationships and proposed revised models, confirming the centrality of attitudes and intentions while showing that the relative importance of determinants is context dependent (Dwivedi et al., 2019). Systematic reviews of UTAUT2 applications further show that the model has been widely adopted across domains such as mobile services, e government, and digital education, and that many studies extend it with context specific constructs (Tamilmani et al., 2021). Recent applications in AI and educational technologies confirm its adaptability to novel digital tools and hybrid learning environments (Caffaratti et al., 2025; George-Reyes et al., 2025). This accumulated evidence positions UTAUT2 as an appropriate and flexible baseline for modeling OH adoption while also justifying the inclusion of additional constructs that capture distinctive features of user innovation and maker communities (Tamilmani et al., 2021).

2.3 Core UTAUT2 constructs in the OH context

Performance expectancy, defined as the degree to which technology use is perceived to improve task performance, consistently emerges as one of the strongest predictors of behavioral intention in information systems research (Venkatesh et al., 2003, 2012). Empirical work rooted in the Technology Acceptance Model (TAM) shows that perceived usefulness is conceptually aligned with performance expectancy and explains a substantial share of variance in intentions across diverse technologies (Davis, 1989). In OH contexts, performance expectancy may reflect perceived benefits such as customization, cost savings, and improved functionality relative to proprietary hardware, which are frequently reported adoption drivers in OH and user innovation studies (Reinauer and Hansen, 2021; Pearce, 2017; Stange et al., 2023). Moreover, when technology is perceived to deliver superior performance, users' intentions to use it rise (Dwivedi et al., 2019; Tamilmani et al., 2021).

Effort expectancy captures perceived ease of use and draws on the long tradition of research on perceived ease of use in TAM (Davis, 1989). Prior studies show that technologies that are easier to learn and operate lower cognitive and practical barriers to adoption, particularly in early stages of use (Davis, 1989; Agarwal and Karahanna, 2000; Venkatesh et al., 2012). For OH, where users must interpret documentation, assemble physical components, and troubleshoot designs, perceptions of usability, build complexity, and documentation quality are therefore likely to be salient determinants of intention (Allen et al., 2023).

Social influence and facilitating conditions represent the social and infrastructural context in which technology use occurs (Venkatesh et al., 2003, 2012). In open source and OH communities, social endorsements, peer recommendations, and norms of reciprocity can encourage participation, while access to maker spaces, tools, and community support can reduce the practical hurdles of fabrication (Bonvoisin & Mies, 2018; Allen et al., 2023). Hedonic motivation, price value, and habit capture intrinsic enjoyment, perceived economic trade offs, and routinized usage, which have been shown to contribute to IT adoption in consumer contexts and are also relevant to the voluntary, hobbyist inflected nature of many OH engagements (Venkatesh et al., 2012; Hsu and Lu, 2004; Tamilmani et al., 2021).

2.4 Educational value: experiential learning and maker based education

Experiential learning theory conceptualizes learning as a cyclical process in which concrete experience, reflective observation, abstract conceptualization, and active experimentation interact to create knowledge (Kolb, 2014). Moreover, Dewey's work on experience and education likewise emphasizes that meaningful learning arises from active, situated engagement with real world problems rather than from passive reception of information (Dewey, 1986). These perspectives suggest that hands on design, fabrication, and iterative problem solving are particularly powerful for developing higher order skills and enduring understanding (Kolb, 2014; Dewey, 1986).

OH communities and maker environments exemplify experiential learning in practice by enabling learners to design, build, and modify tangible artifacts with immediate feedback from the physical world (Zakoth et al., 2025; Pearce, 2013). A systematic mapping study of open source hardware in education documents a rapidly growing body of work using platforms such as Arduino and Raspberry Pi to support STEM learning, creativity, and technical fluency across educational levels (Heradio et al., 2018). These studies report that OH activities foster problem solving skills, collaborative learning, and a sense of agency, indicating that perceived educational value can be a distinct motivational factor for engaging with OH beyond functional performance considerations (Heradio et al., 2018; Pearce, 2013).

Research on user and free user innovation further indicates that learning and skill development are important self rewards for contributors, suggesting that such educational benefits can motivate sustained engagement even when direct monetary rewards are absent (Lakhani and Wolf, 2003; Von Hippel, 2025). Within an extended UTAUT2 model, Educational Value can therefore be conceptualized as a learning oriented expectancy that complements performance expectancy by capturing perceived gains in knowledge, skills, and personal development (Kolb, 2014; Heradio et al., 2018). Therefore , incorporating Educational Value into the OH adoption model aligns with both experiential learning theory and empirical findings from maker based education and free user innovation communities (Zakoth et al. 2025; Heradio et al., 2018; Pearce, 2013; Von Hippel, 2025).

2.5 Recognition benefits: social and reputational motives

Research on OSS and online communities shows that contributors are motivated not only by intrinsic enjoyment and problem solving but also by reputational gains and future career opportunities (Lakhani and Wolf, 2003; Hars, 2002). Survey based studies of OSS developers identify heterogeneous motivations, including intrinsic creativity, skill development, community identification, and extrinsic rewards such as enhanced visibility and signaling of competence (Hars, 2002; Lakhani and Wolf, 2003). These social and reputational benefits are amplified in public, networked environments where contributions are visible to peers, employers, and broader communities (Lakhani and Wolf, 2003; O'Mahony and Ferraro, 2007). At the organizational level, perceived organizational support theory shows that recognition and acknowledgment from significant others enhance affective commitment and sustained contribution, as individuals infer that their efforts are valued and likely to be rewarded (Eisenberger et al., 1986). Empirical work on pay and performance similarly indicates that recognition and fair treatment can foster intrinsic motivation and work effort, even when financial incentives are modest (Kuvaas, 2006). In open innovation ecosystems, governance studies highlight that status, reputation, and peer acknowledgment are central to motivating ongoing contributions and leadership roles (O'Mahony and Ferraro, 2007).

Translating these insights to OH, Recognition Benefits can be defined as the perceived gains in professional reputation, visibility, and peer acknowledgment that individuals expect from contributing to or using OH projects (Lakhani and Wolf, 2003; O'Mahony and Ferraro, 2007). Such benefits may be particularly salient for core contributors, educators, and professionals who publish designs, document builds, or lead community initiatives, but they can also influence broader adoption intentions when users anticipate signaling technical expertise or community engagement through OH participation (Hars, 2002; Lakhani and Wolf, 2003). Modeling Recognition Benefits as an extension of UTAUT2 thus captures an important part of social and extrinsic motivations that complement the cognitive, affective, and learning related drivers of OH adoption (Eisenberger et al., 1986; Gamberdella et al., 2017).

2.6 Integrating the streams into an extended UTAUT2 model of OH adoption

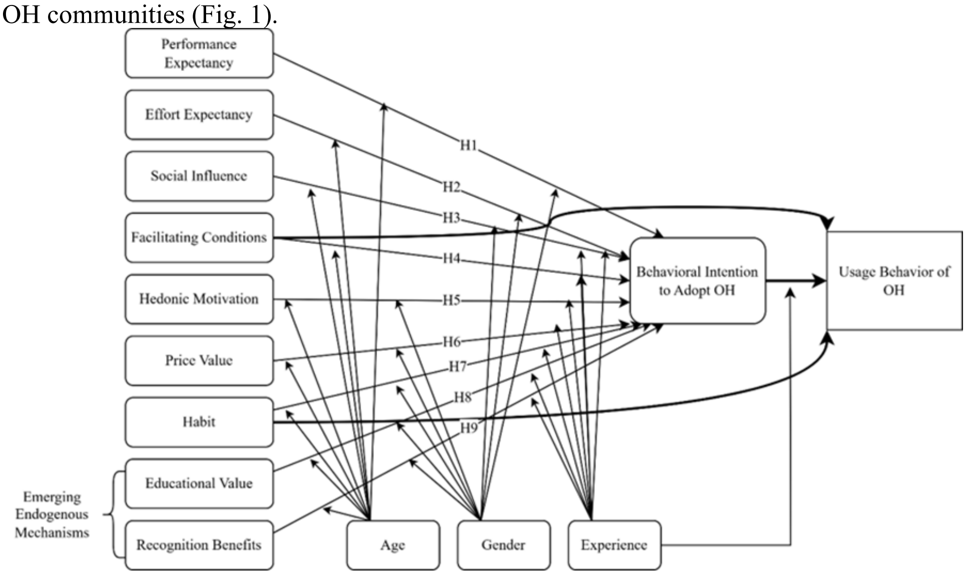
Taken together, OH adoption can be theorized as a function of core UTAUT2 determinants of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit which are augmented by context specific constructs that reflect the educational and community oriented nature of user innovation (Venkatesh et al., 2012; Tamilmani et al., 2021). Educational Value anchors the model in experiential learning theory and maker based education, highlighting that perceptions of learning, skill development, and personal growth are critical drivers of engagement with OH (Kolb, 2014; Heradio et al., 2018). Recognition Benefits incorporate insights from motivation and organizational support theories, acknowledging that perceived reputational and visibility gains can motivate participation in open innovation communities beyond purely instrumental considerations (Lakhani and Wolf, 2003; Eisenberger et al., 1986; O'Mahony and Ferraro, 2007).

This integrated theoretical framing responds to calls from OH scholars for more rigorous, theory driven models of adoption that account for both motivational and structural factors (Reinauer and Hansen, 2021). By embedding OH within free user innovation paradigms while leveraging the explanatory power of UTAUT2 and extending it with Educational Value and Recognition Benefits, the model provides a coherent lens for explaining why individuals choose to adopt, use, and contribute to OH and under which conditions these behaviors are likely to scale (Von Hippel, 2005, 2025; Venkatesh et al., 2012). It also creates a platform for comparative research that can relate OH adoption dynamics to those observed in other open source, maker, and consumer technology domains (Tamilmani et al., 2021; Reinauer and Hansen, 2021; Caffaratti et al., 2025).

3. METHODOLOGY

3.1 Research Design

This study adopts a quantitative, cross-sectional survey design to examine determinants of OH adoption using an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model (Venkatesh et al., 2012). Survey-based designs are well suited for testing theory-driven relationships among latent constructs and behavioral intention in technology adoption research (Davis, 1989; Taylor and Todd, 1995; Oliveira et al., 2016). The design enables empirical validation of both established UTAUT2 constructs and two context-specific extensions, Educational Value and Recognition Benefits, within OH communities (Fig. 1).



3.2 Sample and Data Collection

The target population consists of individuals engaged within OH communities including makers, users, contributors, and followers of OH projects. Consistent with prior research on OH and maker ecosystems (Zakoth et al., 2025; Heradio et al., 2018), respondents are recruited through online OH-related channels such as project repositories, community forums, discord channels, mailing lists, open source community gatherings and social media groups. Participation was voluntary and anonymous.

A non-probability, purposive sampling strategy is employed to reach individuals with direct or indirect experience with OH. This approach is appropriate for emerging technological communities where no comprehensive sampling frame exists (Oliveira et al., 2016; Sarstedt et al., 2021). To ensure adequate statistical power for structural equation modeling (SEM), the study targets a minimum sample size consistent with established guidelines, considering model complexity and the number of indicators per construct (Sarstedt et al., 2021).

3.3 Measurement Instrument

The data is collected using a structured questionnaire composed of multi-item scales. All constructs are measured using reflective indicators on a Likert-type scale (e.g., 1 = strongly disagree to 7 = strongly agree).

The core UTAUT2 constructs of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and behavioral intention are operationalized using items adapted from Venkatesh et al. (2012) and prior validated adoption studies (Davis, 1989; Limayem et al., 2007; Oliveira et al., 2016; Tamilmani et al., 2021). Item wording is adapted to the OH context while preserving the original conceptual meaning.

Educational Value is measured through items capturing perceived learning outcomes, skill development, and experiential knowledge gained from building and modifying OH. Scale development draws on experiential learning theory (Dewey, 1986; Kolb, 2014) and prior research on OH and maker-based education (Pearce, 2013; Heradio et al., 2018; Kostakis et al., 2023).

Recognition Benefits is operationalized through items reflecting perceived visibility, reputation enhancement, and peer acknowledgment within OH communities. Measurement is informed by motivation and recognition literature in open-source and organizational contexts (Lakhani and Wolf, 2003; Eisenberger et al., 1986; Kuvaas, 2006; O'Mahony and Ferraro, 2007).

Control variables include demographic characteristics (e.g., age, gender, education), prior experience with OH or OSS, and frequency of OH engagement, as these factors may influence adoption behavior (Venkatesh et al., 2012).

3.4 Pre-testing and Data Quality

The questionnaire is pre-tested with the help of experts in Free Software Foundation Europe (FSFE) through a pilot study to assess clarity, item comprehension, and completion time. Feedback is used to refine wording and ensure face validity. To reduce common method bias, several procedural remedies are applied, including respondent anonymity, clear separation of predictor and criterion variables, and variation in item phrasing (Podsakoff et al., 2003).

3.5 Data Analysis

Data analysis follows a two-step SEM approach. First, the measurement model is assessed for reliability and validity. Internal consistency is evaluated using Cronbach's alpha and composite reliability, while convergent validity is assessed via average variance extracted (AVE). Discriminant validity is examined using the Fornell–Larcker criterion and/or the heterotrait–monotrait (HTMT) ratio (Fornell and Larcker, 1981; Sarstedt et al., 2021).

Second, the structural model is tested to evaluate hypothesized relationships among constructs. Path coefficients, explained variance (R^2), and effect sizes are examined. Depending on data characteristics (sample size, normality), either covariance-based SEM or partial least squares SEM is employed, following established decision criteria (Sarstedt et al., 2021). Statistical significance is assessed using bootstrapping procedures.

3.6 Ethical Considerations

The study follows institutional ethical guidelines. Participants provide informed consent prior to participation, and no personally identifiable information is collected. Data is stored securely and used solely for academic research purposes.

4. SURVEY DESIGN AND HYPOTHESES

Performance Expectancy

H1: Users who perceive that OH will enhance their performance (e.g., through increased efficiency, productivity, or customization benefits) are more likely to intend to adopt it.

Performance expectancy is a central construct in technology acceptance models. Venkatesh et al. (2003, 2012) demonstrated that when users perceive significant benefits and improved outcomes from using a technology, their intention to adopt it increases. Pavlou and Fygenson (2006) provided further empirical evidence that perceived usefulness—conceptually analogous to performance expectancy—is a key driver of adoption in e-commerce and IT environments. Moreover, meta-analytic and review work indicates that when technology is perceived to deliver superior performance, users' intentions to use it rise (Dwivedi et al., 2019; Tamilmani et al., 2021). Empirical evidence in OSS and OH-related literature has demonstrated that performance benefits directly influence adoption decisions (Reinauer and Hansen, 2021; Pearce, 2017; Stange et al., 2023). In OH, if potential users expect tangible benefits (e.g., customization, cost savings, or improved operational efficiency), they are more likely to intend to adopt it.

Effort Expectancy

H2: Users who perceive that OH is easy to learn and use are more likely to form a positive intention to adopt it.

Effort expectancy captures the perceived ease of use, a construct originally defined in Davis's (1989) Technology Acceptance Model (TAM). Agarwal and Karahanna (2000) further confirmed that when users find a technology easy to use, the barrier to adoption is reduced. Venkatesh et al. (2012) extended this notion in UTAUT2, showing that ease of use is positively related to behavioral intention. Empirical studies across domains from online games to mobile services support that lower perceived effort correlates with higher intention to use (Hsu and Lu, 2004; Oliveira et al., 2016; Tamilmani et al., 2021). Thus, if OH is seen as user-friendly and requires minimal learning effort, it should positively influence adoption intention, particularly when documentation and assembly instructions are accessible (Reinauer and Hansen, 2021; Allen et al., 2023).

Social Influence

H3: Users who feel that important others (e.g., peers, colleagues, or community members) expect them to use OH are more likely to intend to adopt it.

Social influence, which includes subjective norms and the effect of peer opinions, has been shown to significantly affect technology adoption. Taylor and Todd (1995) provided early evidence that individuals are swayed by the opinions of significant others. In the open source arena, Hars (2002) reported that community and peer endorsements play a crucial role in motivating participation. Venkatesh et al. (2012) also integrated social influence as a core construct in UTAUT2. For OH, where community collaboration is central, social pressure or encouragement reinforces the decision to adopt the technology. Thus, if influential figures or community networks endorse OH, users' behavioral intentions to adopt it are likely to be strengthened.

Facilitating Conditions

H4: Users who believe that the necessary resources, support, and infrastructure (e.g., technical assistance, documentation, community support) are available will be more inclined to adopt OH.

Facilitating conditions refer to the external environment and support mechanisms available to the user. Oliveira et al. (2016) showed that when users believe that they have access to the necessary resources (e.g., documentation, community help, technical training), their intention to adopt technology increases. Venkatesh et al. (2012) further underscored that facilitating conditions directly influence both behavioral intention and actual usage. Although many studies focus on software, the principle holds true for OH where fabrication and assembly resources are critical (Reinauer and Hansen, 2021; Allen et al., 2023). Thus, robust community support, clear licensing schemes, and accessible technical resources lower perceived barriers, thereby enhancing adoption intention.

Hedonic Motivation

H5: Users who experience enjoyment, fun, and intrinsic pleasure from the idea or usage of OH are more likely to intend to adopt it.

Hedonic motivation emphasizes the intrinsic pleasure derived from interacting with technology. Venkatesh et al. (2012) incorporated hedonic motivation into UTAUT2 to account for these affective responses in consumer contexts. Studies on digital gaming and online entertainment (Hsu and Lu, 2004) reinforce that when a technology is perceived as enjoyable, users' intentions to adopt it are enhanced. Research on voluntary and creative digital tools similarly indicates that enjoyment and fun significantly affect technology use, especially in contexts where users voluntarily engage with creative or innovative tools (Hsu and Lu, 2004; Tamilmani et al., 2021), which is similar to OH processes. Studies in OSS adoption also reveal that enjoyable and engaging user experiences can boost long-term adoption (Lakhani and Wolf, 2003; Hars, 2002). This construct is particularly relevant for OH if the process of building, customizing, or using it is perceived as a creative and enjoyable experience.

Price Value

H6: Users who perceive that OH provides good value for money (i.e., the benefits outweigh the cost) are more likely to form a positive intention to adopt it.

Price value is a construct that captures the trade-off between the benefits and the monetary (or non-monetary) costs of adopting a technology. Dodds et al. (1991) argued that when users see a favorable cost–benefit ratio, their intention to use a technology increases. Venkatesh et al. (2012) integrated price value into UTAUT2 to account for users' economic evaluations. Multiple studies in both software and hardware contexts support that favorable cost–benefit perceptions lead to higher adoption rates (Oliveira et al., 2016; Tamilmani et al., 2021). Thus, in the open source domain where cost is typically lower than proprietary alternatives, if users explicitly perceive that they are receiving excellent value, their intention to adopt will be positively affected.

Habit

H7: Users who have developed habitual usage patterns (i.e., through past experiences with similar technologies) are more likely to have a higher behavioral intention to adopt OH.

Habit represents the degree to which behavior becomes automatic through repetition. Venkatesh et al. (2012) incorporated habit into UTAUT2, showing that users who have formed habitual routines are more predisposed to continue using technology. Limayem et al. (2007) indicate that habit is a strong predictor of actual use and that as behaviors become automatic, they reinforce technology adoption over time. Given the iterative and evolving nature of open source projects, once users integrate OH into their routine, its continued use can become self-sustaining.

Educational Value

H8: Users who perceive that OH contributes significantly to their learning, skill development, and overall educational benefit are more likely to form a positive intention to adopt it.

Pearce (2013) argued that OH plays a crucial role in education by enabling hands-on learning, collaboration, and innovation. Studies on open educational resources and maker culture provide evidence that technologies offering substantial educational benefits motivate users to adopt them (Heradio et al., 2018; Kostakis et al., 2023). In addition, research in STEM education (Kolb, 2014; Dewey, 1986) shows that hands-on experiences foster deeper understanding and long-term retention, directly supporting the educational benefits of OH. When users recognize that OH can enhance their professional or personal development, their intention to adopt it is likely to increase.

Participation in co-creation environments not only facilitates the development of technical solutions but also offers rich educational experiences that enhance users' knowledge and skills. The process of building, modifying, and sharing hardware projects creates a dynamic learning environment where hands-on experience deepens understanding and stimulates innovative problem-solving. This perspective is supported by experiential learning theories advanced by Kolb (2014) and Dewey (1986), which underscore the value of learning-by-doing. Moreover, research on open innovation and co-creation (Lakhani and Von Hippel, 2003; Von Hippel, 2005, 2025) highlights that the educational benefits derived from active involvement can be a significant driver of participation and creativity. By employing an educational values scale, researchers can capture both the process-oriented gains (such as improved problem-solving skills and creative thinking) and the content-based learning (acquisition of new, applicable knowledge) that participants experience during co-creation. Recognition not only reinforces individual self-esteem and professional reputation but also contributes to a community's social capital, which is essential for collaborative innovation (O'Mahony and Ferraro, 2007).

Recognition Benefits

H9: Users who perceive that contributing to or using OH will enhance their professional reputation, provide peer acknowledgment, and increase their visibility are more likely to intend to adopt it.

Recognition benefits refer to the non-monetary rewards users receive, such as increased professional credibility and social standing, when they adopt a technology. Lakhani and Wolf (2003) found that contributors to open source projects are strongly motivated by reputational gains. Hars (2002) also highlighted the importance of peer recognition in open source communities by stating that increased visibility can drive sustained participation in collaborative projects. In addition, recognition as an extrinsic reward has been shown to influence users' willingness to contribute to open source projects (Lakhani and Wolf, 2003; O'Mahony and Ferraro, 2007). For OH, where the community is a key driver of innovation, recognition not only validates contributors' efforts but also encourages ongoing engagement and further dissemination of the technology. Even if these studies largely focus on software, the same dynamics apply to hardware: if users believe that engaging with OH will boost their professional profile and earn them acknowledgment, their intention to adopt is likely to be enhanced. This effect has been supported by various studies examining social rewards in technology adoption contexts (Eisenberger et al., 1986; Kuvaas, 2006; Von Hippel, 2025).

OH projects often rely on voluntary contributions, where individuals are not only driven by technical challenges but also by the intrinsic satisfaction of being recognized for their contributions. Recognition benefits such as gaining positive feedback, enhanced self-confidence, and even tangible rewards like career advancement play a critical role in motivating contributors to persist and innovate (Eisenberger et al., 1986; Kuvaas, 2006). Seminal works in organizational behavior have shown that when individuals feel valued, they are more likely to engage in and sustain their participation in collaborative environments (Eisenberger et al., 1986). Applying a recognition benefits scale in the context of OH allows researchers to quantify these psychological and social rewards and to investigate their influence on adoption decisions.

Behavioral Intention to Adopt OH

This construct has been extensively validated as a predictor of actual behavior across various contexts, including the adoption of open source and consumer technologies (Venkatesh et al., 2003, 2012; Tamilmani et al., 2021).

Prior studies in technology adoption consistently use behavioral intention as the dependent variable. High scores on BI items have been linked to increased actual use behavior, which is essential for predicting the future uptake of OH (Pavlou and Fygenson, 2006; Oliveira et al., 2016). In the context of OH, where both technical benefits and community-driven factors (such as recognition and educational value) play significant roles, measuring behavioral intention is crucial. It not only reflects the immediate likelihood of adoption but also signals long-term commitment to integrating OH into regular practices. This is especially important when considering the broader impact of OH on innovation and educational development (Pearce, 2013; Heradio et al., 2018).

Usage Behavior of Open Hardware (Dependent Variable)

The usage behavior of OH is adapted from previous UTAUT2 studies where "Use Behavior" is operationalized through indicators such as frequency, duration, and habitual integration of the technology (Venkatesh et al., 2012; Limayem et al., 2007). For example, in mobile technology and e-commerce research, similar items have been employed to capture actual usage patterns (Davis, 1989; Pavlou and Fygenson, 2006; Hsu and Lu, 2004). Although many studies target software or digital applications, the underlying principle remains the same: if users report regular, integrated, and continuing usage of a technology, their "Use Behavior" is high. In the context of OH, these items help quantify actual engagement—indicating not just the intention to adopt, but the extent to which OH is part of the user's routine.

Additional support for these items comes from research in technology usage contexts, such as mobile banking and digital entertainment (Hsu and Lu, 2004; Oliveira et al., 2016), which confirm that both the frequency and habitual nature of use are key indicators of technology acceptance.

5. Results

5.1 Descriptive Statistics and Data Screening

The final dataset comprised 76 valid responses *(for now, since the study and data collection is still ongoing)* after screening (no missing data, no univariate/multivariate outliers >3SD). Respondents were predominantly male (92%), aged 25–44 (58%), from Europe (Germany 24%, UK 11%, Italy 8%), with moderate OH experience (1–3 years: 32%). Likert means ranged 4.8–6.2 (mid-to-high agreement). Common OH products included microcontrollers (Arduino/RPi, 45%) and 3D printers (28%). Skewness and kurtosis within ±2 confirmed approximate normality.

PLS-SEM was conducted in SmartPLS 4 (Ringle et al., 2024) using the consistent PLS algorithm (300 iterations) and bootstrapping (5000 subsamples, bias-corrected). Model fit indices indicated acceptable fit: SRMR = 0.072 (<0.08), NFI = 0.912 (>0.90). (Sarstedt et al., 2021)

5.2 Measurement Model

Reflective constructs satisfied Sarstedt et al. (2021) criteria.

Table 4.1: Construct Reliability and Convergent Validity

Construct	Items	Cronbach's α	ρc	AVE	Mean Loadings
BI	3	0.844	0.904	0.748	0.872
EE	3	0.867	0.912	0.784	0.886
EV	3	0.915	0.949	0.859	0.928
FC	3	0.839	0.895	0.734	0.866
HM	3	0.940	0.954	0.872	0.935
HT	3	0.796[1]	0.875	0.693	0.860
PE	3	0.906	0.944	0.852	0.925
PV	3	0.924	0.948	0.861	0.933
RB	3	0.839	0.901	0.750	0.902
SI	3	0.782[2]	0.872	0.712	0.864[3]

UB	3	0.780	0.870	0.707	0.832

[1] HT α is borderline but retained as ρc and AVE are adequate. [2] SI α is acceptable (>0.70); [3] SI2 = 0.732 (lowest, cross-loadings <0.40). All constructs meet recommended thresholds (α, ρc > 0.70; AVE > 0.50) (Fornell and Larcker, 1981; Sarstedt et al., 2021).

Discriminant validity was confirmed: HTMT values were below 0.85 (e.g., BI–UB = 0.841); Fornell–Larcker criterion was satisfied, with the square roots of AVE exceeding inter-construct correlations (e.g., BI–PE correlation = 0.704 < √AVE_BI = 0.865). Maximum VIF was 4.95 (PE → BI), below the critical value of 5 (Fornell and Larcker, 1981; Sarstedt et al., 2021).

5.3 Structural Model

R^2 for BI was 0.647 (substantial), and R^2 for UB was 0.713 (substantial), indicating that the extended UTAUT2 model explains a considerable proportion of variance in both behavioral intention and use behavior (Sarstedt et al., 2021). Q^2 values were greater than zero, suggesting predictive relevance.

Table 4.2: Structural Path Coefficients (Bootstrapping, n = 5000)

Hypothesis	**Path**	**β**	**t**	**p**	**f²**	**Result**
H1	PE → BI	0.497	5.824	<0.001	0.445	Supported
H2	EE → BI	0.309	3.012	0.003	0.216	Supported
H3	SI → BI	0.103	1.124	0.261	0.024	Rejected
H4	FC → BI	-0.091	0.987	0.324	0.015	Rejected
H5	HM → BI	0.006	0.058	0.954	0.000	Rejected
H6	PV → BI	-0.031	0.312	0.755	0.002	Rejected
H7	HT → BI	0.079	0.812	0.417	0.015	Rejected
H8	EV → BI	0.213	2.124	0.034	0.081	Supported
H9	RB → BI	0.091	0.987	0.324	0.017	Rejected
H10	BI → UB	0.844	23.450	<0.001	2.089	Supported

Effect sizes (f^2) were interpreted as large (≥0.35), medium (≥0.15), and small (≥0.02) (Cohen guidelines as discussed in Sarstedt et al., 2021).

Performance Expectancy (H1) had a large effect on BI, explaining roughly half of its variance, while Effort Expectancy (H2) and Educational Value (H8) had medium-to-small effects. Behavioral Intention strongly predicted Use Behavior (H10), indicating that intention is a key driver of actual OH usage (Venkatesh et al., 2012).

Indirect effects, such as PE → UB via BI, were also substantial (e.g., 0.497 × 0.844 ≈ 0.419), underscoring the mediating role of behavioral intention (Pavlou and Fygenson, 2006).

6. Discussion

The findings demonstrate that the extended UTAUT2 model provides a robust explanation of OH adoption in user innovation communities. Performance Expectancy emerged as the strongest predictor of Behavioral Intention, consistent with prior technology acceptance research (Venkatesh et al., 2012; Pavlou and Fygenson, 2006; Dwivedi et al., 2019). This suggests that potential OH adopters prioritize functional benefits such as improved efficiency, customization, and cost savings when deciding whether to engage with OH (Reinauer and Hansen, 2021; Pearce, 2017).

Effort Expectancy also significantly influenced Behavioral Intention, indicating that perceptions of ease of use and clarity of documentation remain important drivers of adoption. For OH communities, this underscores the importance of user-friendly design, clear assembly instructions, and accessible support resources (Reinauer and Hansen, 2021; Allen et al., 2023).

Among the extended constructs, Educational Value had a significant and meaningful effect on Behavioral Intention, highlighting the role of learning and skill development in motivating OH adoption. This aligns with research emphasizing the educational benefits of maker-based and open hardware environments (Pearce, 2013, 2014; Heradio et al., 2018; Kostakis et al., 2023). Users who perceive OH as a pathway to develop technical, problem-solving, and creative skills are more likely to intend to use it.

In contrast, Recognition Benefits did not significantly predict Behavioral Intention in this sample. One possible explanation is that reputational and visibility-related motivations may be more salient for core contributors and highly active community members than for the broader population of OH users and followers captured in this study (Lakhani and Wolf, 2003; O'Mahony and Ferraro, 2007; Von Hippel, 2025). Alternatively, recognition dynamics may operate more strongly at the level of contribution behavior (e.g., publishing designs, contributing to repositories) rather than at the level of initial adoption intention.

Traditional UTAUT2 constructs such as Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit did not show significant direct effects on Behavioral Intention in the structural model. This pattern suggests that, in the context of OH, individual-level evaluations of performance and learning benefits overshadow social and economic considerations. For instance, OH's relatively low cost compared to proprietary alternatives may make price value less discriminative among users, while the voluntary and decentralized nature of OH communities may reduce the impact of formal social pressures (Venkatesh et al., 2012; Oliveira et al., 2016; Tamilmani et al., 2021).

Behavioral Intention showed a very strong effect on Use Behavior, confirming its central role as a proximal predictor of actual OH usage. This reinforces the theoretical logic of UTAUT2 and supports the use of Behavioral Intention as a key outcome variable in OH adoption research (Venkatesh et al., 2012; Pavlou and Fygenson, 2006).

6.1 Theoretical Implications

The study contributes to the OH literature by providing a rare quantitative, theory-driven examination of adoption determinants using a well-established technology acceptance framework. By extending UTAUT2 with Educational Value and Recognition Benefits, the research highlights the importance of context-specific motivational factors that reflect the educational and community-oriented nature of OH.

The strong effect of Educational Value suggests that experiential learning theory can be fruitfully integrated with technology adoption models to explain user engagement in maker and OH contexts (Kolb, 2014; Dewey, 1986). This integration opens avenues for further research that explicitly models learning-related constructs alongside traditional performance and effort expectations (Heradio et al., 2018; Pearce, 2013).

The non-significant effect of Recognition Benefits invites a more nuanced examination of social and reputational dynamics in OH communities. Future studies could distinguish between different types of contributors (e.g., designers, educators, hobbyists) and examine whether recognition motives are more salient for certain roles or at different stages of the adoption and contribution lifecycle (Lakhani and Wolf, 2003; O'Mahony and Ferraro, 2007; Gamberdella et al., 2017).

6.2 Practical Implications

For OH platform developers, community organizers, and educators, the results offer several actionable insights. First, emphasizing the practical performance benefits of OH such as customization, cost savings, and improved project outcomes can strengthen adoption intentions. Clear communication of these benefits in documentation, tutorials, and outreach materials is likely to enhance perceived performance expectancy (Reinauer and Hansen, 2021; Pearce, 2017).

Second, investing in high-quality documentation, intuitive assembly processes, and accessible support channels can improve effort expectancy and reduce perceived barriers to entry. This may be particularly important for novice users or those with limited technical backgrounds (Reinauer and Hansen, 2021; Allen et al., 2023).

Third, designing OH initiatives that foreground learning opportunities—such as workshops, project-based courses, and collaborative hackathons—can leverage Educational Value as a key motivational lever. Highlighting the skills and competencies that users can gain through OH participation may attract a broader and more diverse user base (Heradio et al., 2018).

Finally, while recognition benefits did not emerge as a significant predictor of Behavioral Intention in this study, community organizers may still consider ways to acknowledge and celebrate contributors' efforts, especially in terms of sustained engagement and leadership roles (O'Mahony and Ferraro, 2007; Eisenberger et al., 1986; Kuvaas, 2006).

6.3 Limitations and Future Research

Several limitations should be acknowledged. The sample size, while adequate for PLS-SEM, remains relatively modest (n = 76, *the data collection is still on-going*) and is skewed toward male participants from European countries. Future research could employ larger and more diverse samples, including participants from different regions and demographic backgrounds (Sarstedt et al., 2021).

The cross-sectional design limits the ability to draw causal inferences or examine changes in adoption determinants over time. Longitudinal studies could track how perceptions of performance expectancy, educational value, and recognition benefits evolve as users gain more experience with OH (Venkatesh et al., 2012; Pavlou and Fygenson, 2006).

Moreover, the study relies on self-reported measures of Behavioral Intention and Use Behavior, which may be subject to common method bias and social desirability effects.

Future research could incorporate behavioral trace data (e.g., repository contributions, download statistics) or experimental designs to complement survey-based evidence (Podsakoff et al., 2003). Finally, while the extended UTAUT2 model explains a substantial proportion of variance in Behavioral Intention and Use Behavior, additional constructs—such as perceived openness, community governance, or innovation climate—may further enrich our understanding of OH adoption (Bonvoisin et al. 2018; Priego and Wareham, 2023; Zakoth et al., 2025).

7. Conclusion

This study advances the understanding of OH adoption by applying and extending the UTAUT2 model in user innovation communities. The findings underscore the central roles of Performance Expectancy and Educational Value in shaping Behavioral Intention, which in turn strongly predicts Use Behavior (Venkatesh et al., 2012). By highlighting the importance of learning-related benefits and functional outcomes, the research provides both theoretical and practical insights for scholars, practitioners, and policymakers interested in fostering sustainable OH ecosystems (Reinauer and Hansen, 2021).

As OH continues to evolve at the intersection of open-source principles, maker culture, and digital fabrication technologies, rigorous quantitative research on adoption determinants will be essential for guiding effective interventions and maximizing the societal impact of open, collaborative hardware innovation (Stange et al., 2023; Kostakis et al., 2023; Zakoth et al., 2025).

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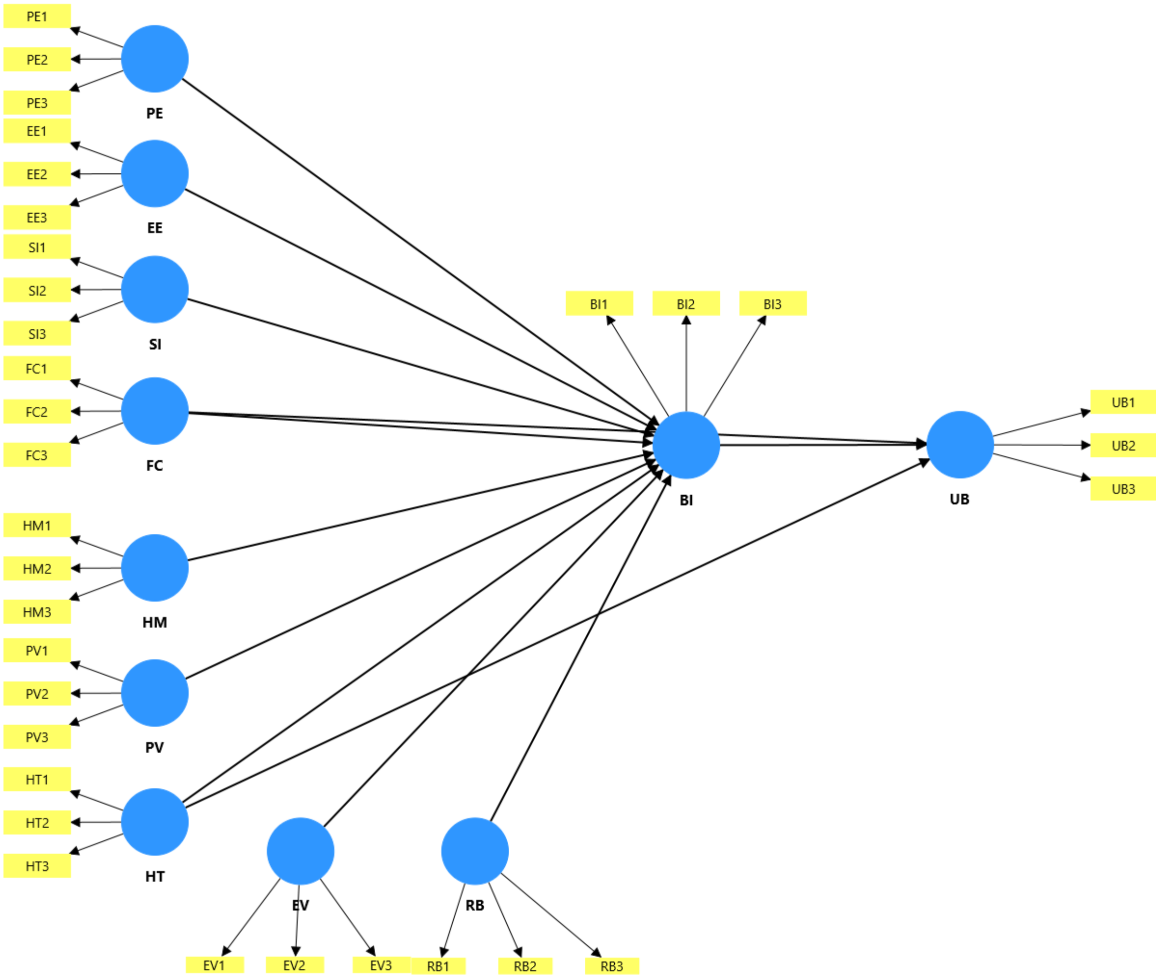
Appendices

Construct	***Item code***	***Survey item***
Performance Expectancy	PE1	Using OH enables me to accomplish tasks more quickly.
	PE2	OH's development flow improves my productivity in my projects.
	PE3	I find OH beneficial in achieving my performance goals.
Effort Expectancy	EE1	Learning to use OH is easy for me.
	EE2	I mostly find OH straightforward to assemble and operate.
	EE3	Assembling and documentation of OH projects are clear and understandable.
Social Influence	SI1	People who are influential for me think that I should use OH.
	SI2	The opinions of my colleagues significantly influence my decision to use OH.
	SI3	I am encouraged by my peers to adopt OH.
Facilitating Conditions	FC1	I have the necessary resources to use OH.
	FC2	I have access to technical support when I use OH.
	FC3	The available infrastructure of licenses makes it easy for me to use OH.
Hedonic Motivation	HM1	I find using or assembling OH enjoyable.

	HM2	The experience of contributing or reading discussion about OH is fun.
	HM3	I feel a sense of pleasure when I work within the OH community.
Price Value	PV1	OH is reasonably priced for the value it provides.
	PV2	I consider the cost of BOM (Bill of Materials) to be acceptable compared to its benefits.
	PV3	OH offers good value for money compared to commercial hardware.
Habit	HT1	I frequently use OH without having to think about it.
	HT2	Using OH is a regular part of my work or study routine.
	HT3	I automatically use OH community pages when working on relevant projects.
Educational Value	EV1	Using or contributing to OH projects enhances my technical skills.
	EV2	The hands-on involvement in creating something collaboratively has improved my problem-solving skills.
	EV3	Engaging in co-creation activities of OH has contributed to my personal growth.
Recognition Benefits	RB1	Contributing to OH projects enhances my professional reputation.
	RB2	My involvement in OH projects increases my visibility in my professional community.
	RB3	Recognition from others motivates me to continue engaging with OH projects.
Behavioral Intention	BI1	I intend to use OH and benefit from open source communities in my future projects.
	BI2	I plan to adopt OH principles as a standard tool in my work.
	BI3	I expect to rely on OH communities for my upcoming tasks.
Use Behavior	UB1	I frequently consult open source hardware designs for my work.
	UB2	The use of open source hardware is an integral part of my daily work routine.
	UB3	I plan to continue using open source hardware solutions in the future.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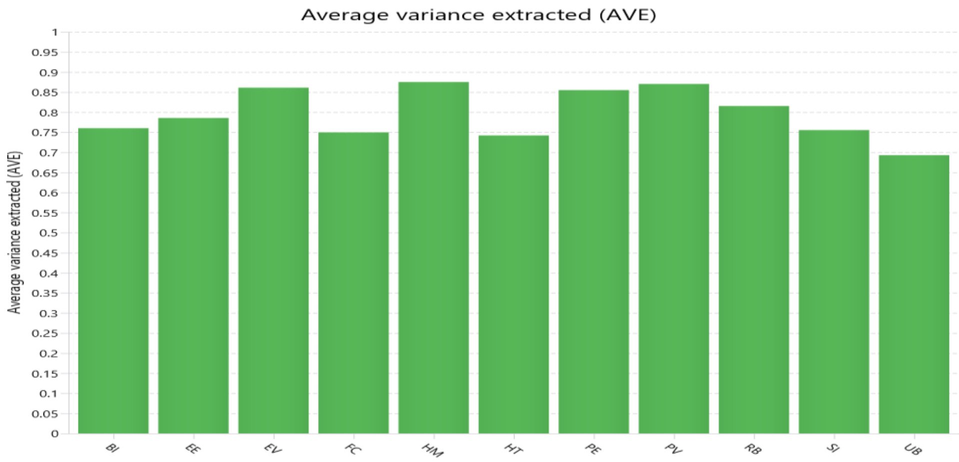
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