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SOCIAL ROBOTS IN HIGHER EDUCATION: FRAMING THE INTEGRATION OF SOCIAL ROBOTS IN HIGHER EDUCATION

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Abstract

This thesis investigates how students and academic staff in German higher education frame the integration of social robots, and how these framings, together with innovation attributes and prior experience, shape the intention to adopt such technologies. The central research question guiding this thesis is: How do students and academic staff in German higher education frame the integration of social robots, and what impact do these frames have on their acceptance of the technology? To address this question, the study draws on framing theory and Rogers' Diffusion of Innovations and applies a quantitative survey design (N = 157).

To answer the first part of the question, the findings show that German respondents, primarily students, as the study faced limitations in collecting data from academic staff, interpret social robots mainly through two competing frames: Innovation, which positions robots as symbols of modernisation, and Gimmick, which frames them as superficial novelties lacking substantive value. While the Assistant and Companion frames received more ambivalent support, the Threat frame was largely rejected, indicating that fears of substitution are not central in the German context.

To address the second part of the question, three hypotheses were formulated, covering the influence of framing (H1), innovation attributes (H2), and prior experience (H3) on adoption. All five frames identified in the literature were systematically tested through hypothesis-driven analyses, not only Innovation and Gimmick. This comprehensive approach ensured conceptual completeness and comparability with prior studies. Hypothesis testing confirmed that framing significantly influences acceptance: positive frames, particularly Assistant ($\rho = .831$, $p < .001$) and Innovation ($\rho = .611$, $p < .001$), increase willingness to adopt, whereas the Gimmick frame strongly reduces it ($\rho = -.571$, $p < .001$). In addition, perceptions of innovation attributes further shape adoption: Relative Advantage ($\beta = .599$, $p < .001$) and Compatibility ($\beta = .460$, $p < .001$) emerged as the strongest predictors, while Image and Observability showed negative effects when overemphasised. Prior experience also proved decisive, with respondents who had interacted with robots reporting substantially higher adoption intentions ($U = 544.50$, $p < .001$). Taken together, the results demonstrate that adoption in German higher education is shaped by framing, perceived usefulness, and prior experience. Robots are most likely to be accepted when framed as innovative or as assistants, and least likely to be adopted when framed as gimmicks.

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List of Abbreviations

ACM	Association for Computing Machinery
AI	Artificial Intelligence
CAGR	Compound Annual Growth Rate
IBM	International Business Machines
IEEE	Institute of Electrical and Electronics Engineers
IFR	International Federation of Robotics
ISO	International Organization for Standardization
IT	Information Technology
MA	Master of Arts
MIT	Massachusetts Institute of Technology
NAO	Humanoid robot developed by SoftBank Robotics
NJ	New Jersey
NY	New York
PARO	Therapeutic Robot Seal
PhD	Doctor of Philosophy
RALL	Robot-Assisted Language Learning
RIG	Robotics Institute Germany
RO-MAN	IEEE International Symposium on Robot and Human Interactive Communication
RQ	Research Question
SDG	Sustainable Development Goals
SPSS	Statistical Package for the Social Sciences
STEM	Science, Technology, Engineering, and Mathematics

USA	United States of America
USD	United States Dollar

1 Introduction

1.1 Relevance of the topic

The global market for educational robots is experiencing rapid expansion, underscoring the increasing relevance of integrating social robots into higher education. According to Grand View Research, based on *the Educational Robot Market Size, Share & Trends Analysis Report by Product, Application, and Region (Grand View Research, 2024a)*, the global educational robots market was valued at USD 1,377.8 million in 2024 and is projected to reach USD 5,842.2 million by 2030, reflecting a compound annual growth rate (CAGR) of 28.8% between 2025 and 2030 (Grand View Research, 2024a).[1] Similarly, Statzon, drawing on the *Global - Educational Robot Market Research Report Forecast to 2032*, forecasts steady growth, estimating that the market will increase from USD 1.288 billion in 2022 to USD 6.061 billion by 2032, corresponding to a CAGR of 16.9% during the period 2023-2032 (Statzon, 2024).[2]

In Germany, the educational robot market demonstrates particularly strong growth potential. Grand View Research (2024b) estimates that revenues reached approximately USD 107.6 million in 2024 and are expected to grow to USD 432.0 million by 2030, with a CAGR of 27.7% between 2025 and 2030 (Grand View Research, 2024b). These forecasts highlight Germany not only as a major European hub for robotics but also as a leading context for the educational deployment of such technologies.

Beyond market reports, institutional and governmental initiatives highlight the growing strategic importance of robotics in education. The Robotics Institute Germany (RIG), supported by the Federal Ministry of Research (BMBF), aims to strengthen Germany's position in AI-powered robotics by fostering academic programs and talent development (Robotics Institute Germany, n.d.). It coordinates university-level training in robotics and AI, including Bachelor's, Master's, and PhD programs, while simultaneously promoting robotics education across schools to increase early exposure (see Robotics Institute Germany, n.d.).

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[1] Author's note: Only publicly available information from the Grand View Research website was used, as the full report is behind a paywall.

[2] Author's note: Only publicly available information from the Statzon website (summary) was used, as the full report is behind a paywall.

Taken together, these trends suggest several key drivers for the integration of social robots in higher education: growing investment in educational technologies and STEM[3]-oriented curricula (Grand View Research, 2024a; Statzon, 2024) and governmental and institutional support for the diffusion of robotics into educational frameworks, particularly in Germany (Robotics Institute Germany, n.d.).

In sum, the empirical market data and strategic policy initiatives indicate that social robots are not merely a niche technological innovation but are becoming a central element in the digital transformation of higher education. Recent academic work further supports this perspective. As Zamora et al. (2025) emphasize, "educational robotics enhances student motivation and engagement, with prediction models reaching an accuracy of 98.78% in assessing academic engagement" (Zamora et al., 2025, p 1). Moreover, their review highlights that social robots and AI-based tutors "demonstrated their potential to personalize learning," while robotic telepresence provides "an effective alternative for hybrid education" (Zamora et al., 2025, p 1). Baena-Rojas et al. (2025) report that students interacting with social robots experienced "increased general interest in class ($\rho = 0.741$, $p < 0.001$) and a faster perception of time ($\rho = 0.679$, $p < 0.001$)" (Baena-Rojas et al., 2025, p. 249). These findings underline the growing academic consensus that social robots can meaningfully contribute to teaching and learning processes in universities.

1.2 Research Gap

Despite rapid market growth and increasing policy interest in educational robotics, as outlined in section 1.1 (Grand View Research, 2024a; Statzon, 2024; Zamora et al., 2025), significant research gaps remain in their integration into higher education. Existing studies show positive effects on motivation, engagement, and skill development (see Zamora et al., 2025; Baena-Rojas et al., 2025), yet little attention has been given to how students and academic staff interpret and frame the role of social robots within universities. These interpretive frames are crucial, as they can shape both acceptance and long-term integration into academic practice.

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[3] STEM is an acronym for Science, Technology, Engineering, and Mathematic*s*, used as a collective label for educational programs, policies, and practices involving these disciplines. It originated in the 1990s at the U.S. National Science Foundation and has since become a central focus in education reform initiatives (Bybee, 2010, *Advancing STEM Education: A 2020 Vision*, p. 30).

And there is still a notable lack of empirical studies examining perceptions and adoption factors among students and staff in German universities.

1.3 Research aim and objectives

The aim of this study is to examine how social robots are perceived and interpreted by students and academic staff in German higher education. The research focuses on understanding the role of individual perceptions and interpretive framing in shaping attitudes toward the integration of these technologies into teaching and learning environments. In doing so, the study seeks to identify the dominant frames through which social robots are evaluated and to explore how specific innovation-related characteristics influence acceptance or resistance. To guide this perspective, the study draws conceptually on Rogers' *Diffusion of Innovations Theory* (2003) and the perception model developed by Moore and Benbasat (1991), which provide established frameworks for analyzing how innovation attributes shape adoption processes. Ultimately, the research aims to contribute to a deeper understanding of the factors that support or hinder the adoption of social robots in German universities and to provide a foundation for future integration strategies.

1.4 Research Question

This study seeks to address the following central research question: **How do students and academic staff in German higher education frame the integration of social robots, and what impact do these frames have on their acceptance of the technology?**

The question aims to explore how social robots are perceived and interpreted within the specific context of German universities. It considers the role of interpretive framing in shaping user attitudes and examines how these frames influence openness to adoption. In order to address this aim, the study develops hypotheses (see Section 2.4) that are empirically tested (see Section 4) using a survey method, enabling a structured examination of the adoption processes.

1.5 Target Group

This study focuses on two primary target groups within German higher education institutions: students and academic staff. These groups represent the central stakeholders in teaching and learning environments and are considered key end-users in the adoption of educational technologies such as social robots. Their perceptions, expectations, and interpretive frames play a crucial role in shaping both individual acceptance and institutional openness toward new technological solutions.

In the context of this research, students and academic staff can also be regarded as potential early adopters of educational innovations. According to the Diffusion of Innovations theory, “the early adopter is considered by many as ‘the individual to check with’ before using a new idea” and plays a central role in decreasing uncertainty and influencing broader acceptance within social systems (Rogers, 2003, p. 309). In the context of higher education, students and academic staff often assume this function, as their initial evaluations and experiences with emerging technologies shape institutional readiness and set the tone for wider adoption.

Beyond these two primary user groups, the study’s findings also hold relevance for university administrators and policymakers, particularly in shaping institutional strategies for digital transformation, as well as for technology developers and designers in the field of social robotics. In this regard, communication strategies constitute an essential dimension, as they determine how social robots are framed and introduced within academic environments, thereby influencing both stakeholder perceptions and adoption dynamics. To establish a solid conceptual foundation for examining these adoption processes, the following chapter outlines the theoretical frameworks and reviews the current state of research on social robots in higher education.

2 Theoretical Framework/Current State of Research

2.1 Defenition and Characteristics of Social robots

2.1.1 General Definition of Robots

In order to contextualize the study and to ground the subsequent empirical analysis, the following section introduces the theoretical frameworks, beginning with a general definition of robots and their characteristics. Robots have been subject to various definitions across disciplines such as engineering, computer science, and the social sciences. A widely accepted baseline is provided by the International Organization for Standardization (ISO). According to ISO 8373:2021 (3.1), a robot is defined as a "programmable actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning" (ISO, 2021, p. 3.1). This definition emphasizes programmability, autonomy, and the capability to interact with the environment, and it is applicable across different types of robots, including industrial robots, service robots, mobile robots, wearable robots, and social robots. The ISO further clarifies in its notes that a robot necessarily includes a control system and can take diverse mechanical forms such as manipulators, mobile platforms, or wearable structures (ISO, 2021, p. 3.1).

Complementing this technical definition, Bekey (2005, p. 2) provides a broader conceptualization, describing a robot as a machine that "senses, thinks, and acts." In this sense, robots integrate three essential components: sensors for perceiving their environment, actuators for performing physical tasks, and control systems (ranging from simple algorithms to artificial intelligence) for decision-making (Bekey, 2005, p. 2). This definition highlights the cybernetic nature of robots and underlines their ability to operate autonomously or semi-autonomously, thereby distinguishing them from simpler automated machines (see Bekey, 2005, p. 2).

Taken together, these definitions illustrate that the concept of a robot extends beyond the purely technical domain of automation. While ISO 8373:2021 provides a universal and precise definition focusing on autonomy and programmability (ISO, 2021, p. 3.1), Bekey (2005, p. 2) adds a systems-oriented view that emphasizes sensing, reasoning, and action. This combined perspective ensures a comprehensive understanding of robots as programmable, sensor-equipped, and autonomous systems. It establishes an understanding that forms the foundation for discussing social robots, which represent the central focus of this study.

2.1.2 What are Social Robots

The shift from general definitions of robots to the more specific category of social robots illustrates an increasing awareness that some robotic systems are developed not just to carry out

practical functions but also to engage in interactions with people and respond to them in socially meaningful ways. As Dautenhahn argues, the field of socially intelligent agents seeks to design robots that exhibit aspects of human-style social intelligence, embedding them in meaningful social contexts (Dautenhahn, 1998, p. 573). One of the earliest and most prominent experiments was Grey Walter's tortoises Elmer and Elsie, created in the late 1940s. These robots exhibited phototaxis by moving toward light sources and, when placed together, appeared to "dancing" around each other, a behavior later interpreted as an elementary form of social interaction between machines (see Fong, Nourbakhsh & Dautenhahn, 2003, p. 144). These early experiments paved the way for a conceptual shift in robotics research, moving from collective behaviors toward individualized social interaction. In subsequent decades, concepts from biology, particularly stigmergy and collective behavior in social insects, were applied to robotics, leading to the emergence of swarm robotics and distributed multi-robot systems (see Fong et al., 2003, p. 144).

A conceptual shift occurred when researchers began to move beyond studying anonymous collectives toward what Fong et al. describe as individualized societies of robots, in which each agent could recognize others, engage in communication, and learn through interaction. Within this framework, Dautenhahn and Billard offered one of the early definitions: "Social robots are embodied agents that are part of a heterogeneous group: a society of robots or humans. They are able to recognize each other and engage in social interactions, they possess histories (perceive and interpret the world in terms of their own experience), and they explicitly communicate with and learn from each other" (Fong et al., 2003, p. 145).

Building on these early insights, Breazeal developed one of the first systematic classifications of social robots. She distinguished between socially evocative robots, which rely on humans' natural tendency to anthropomorphize; social interface robots, which employ human-like cues to provide more natural interactions; socially receptive robots, which passively learn from social input; and sociable robots, which actively seek engagement to satisfy internal drives (see Fong et al., 2003, p. 145). Later contributions expanded this typology with additional categories, including socially situated robots, which perceive and react to their social environment, socially embedded robots, which are structurally coupled with human settings and aware of interactional structures such as turn-taking, and socially intelligent robots, which exhibit aspects of human-like social cognition (see Fong et al., 2003, pp. 145-146). To unify these perspectives, Fong, Nourbakhsh, and Dautenhahn introduced the concept of "socially interactive robots," defined as robots for which social interaction is a central functionality. Such

robots are expected to demonstrate a wide range of human-social characteristics, including the ability to express and perceive emotions, engage in dialogue, maintain relationships, use natural cues such as gaze and gestures, display individual personalities, and develop social competencies over time (see Fong et al., 2003, p. 146).

Alongside these classifications, more formal definitions began to emerge. One of the most frequently cited is provided by Bartneck and Forlizzi, who define a social robot as "an autonomous or semi-autonomous robot that interacts and communicates with humans by following the behavioral norms expected by the people with whom the robot is intended to interact" (Bartneck & Forlizzi, 2004, p. 592). This definition highlights two essential aspects: autonomy and compliance with social norms. Complementing this, Dautenhahn (2007) emphasizes that social robots must not only be autonomous and physically embodied but also capable of interpreting social signals and acting according to cultural and situational norms. These qualities, she argues, distinguish social robots from other interactive technologies by embedding them in meaningful social contexts (see Dautenhahn, 2007, p. 685). Together, these works laid the foundation for the academic understanding of the category "social robot." While Bartneck and Forlizzi stress compliance with social norms, Dautenhahn broadens the framework by highlighting the necessity of cultural adaptation and signal interpretation, thereby shaping the direction of subsequent research in human-robot interaction.

Beyond their conceptual definitions, socially interactive robots are applied in a variety of domains. As Fong, Nourbakhsh, and Dautenhahn (2003, p. 145) observe, such robots can function as research platforms, companions, therapeutic aids, toys, and educational tools (Fong et al., 2003, p. 145). These diverse applications underline the flexibility of social robots to operate across contexts where interaction with humans plays a central role. Given that the present study focuses on the integration of social robots into higher education, it is therefore essential to examine their specific relevance within educational contexts and to explore how they can contribute to teaching and learning practices.

2.1.3 Relevance of Social Robots for Education

Johal (2020) highlights that education has emerged as "one of the most growing areas for commercialization of social robots, foreseen to provide an engaging and personalized learning experience" (Johal, 2020, p. 76). This observation underscores the fact that the educational domain has become a natural and strategically significant setting for the deployment of social robots. Their communicative and adaptive qualities, as outlined in Section 2.1.2, make them particularly well-suited to support teaching and learning environments.

Empirical evidence further supports this potential. Belpaeme et al. (2018) demonstrate that physically embodied robots can serve as tutors or peer learners, producing both cognitive and affective outcomes comparable to those achieved through human tutoring in restricted settings (Belpaeme et al., 2018, pp. 1-2). Their physical embodiment not only strengthens engagement and compliance but also enhances learners' motivation, which is particularly valuable in contexts where personalization and sustained social interaction are critical for educational success (Belpaeme et al., 2018, pp. 2-3).

Finally, large-scale analyses confirm the accelerating academic and societal attention toward educational robotics. Lu et al. (2025) document that the market for educational robotics is expected to rise from USD 1.4 billion in 2022 to USD 3.2 billion by 2027, with a CAGR of 17.3% (Lu et al., 2025, p. 2). This dynamic growth illustrates how social robots align with global educational priorities, including Sustainable Development Goal 4 (Quality Education), by fostering innovation in teaching and supporting equitable access to modern learning tools (United Nations, 2015). The relevance of social robots in education is twofold: they represent a fast-growing industry with significant economic impact, and they provide clear pedagogical and research value through their capacity to enhance engagement, personalization, and learning outcomes.

Based on these conceptual and empirical foundations, it is important to identify which social robots are most frequently used in educational contexts. Reviewing concrete examples helps to connect the abstract definitions and market trends discussed above with the actual technologies shaping current teaching and learning practices.

Examples of Social Robots

Among the wide range of platforms currently available, two robots stand out as the most widely used in higher education: Pepper and Nao. Both were developed by SoftBank Robotics and have become central in educational research and practice due to their versatility, programmability, and expressive capabilities. A recent survey of applications in educational contexts confirms that these two humanoid platforms are the most frequently employed in teaching assistance, language learning, and related tasks (Youssef, Said, Al Kork & Beyrouthy, 2023, p. 73).

Pepper, with its integrated touchscreen and multimodal interaction abilities, has been used to design robot-supported learning environments that increase motivation, attention, and concentration among university students. Field studies in Germany, for example, have shown that students perceive Pepper as an engaging and motivating tutor, adding value beyond

traditional self-study or digital tools (Donnermann, Schaper & Lugrin, 2020, pp. 1-2). Similarly, Nao has been widely applied as a teaching assistant and in language learning scenarios, where its compact size and rich set of expressive behaviors make it particularly suitable for interactive learning situations (Youssef et al., 2023, p. 73).

To complement these insights with a more systematic overview, it is useful to examine the range of robotic platforms that have been documented in recent educational research. Various robots differ not only in their physical embodiment but also in their technical capabilities and pedagogical applications, which influence the ways in which they are integrated into teaching and learning contexts. Table 1 provides a structured summary of some of the most frequently utilized social robots in education, outlining their shapes, core functionalities, and typical usage scenarios.

Table 1 Robotic platforms used in education: shapes, characteristics, and applications

Robot	**Shape**	**Capabilities**	**Usage**
Nao	Humanoid	Multiple degrees of freedom ouch, sound and image sensor imbedded speech recognition an dialogue, programmable, etc	Teaching assistance Language learning
Pepper	Humanoid	Multiple degrees of freedom Touch, sound and image sensors Embedded speech recognition and dialogue, programmable, ete.	Language learning
Furhat	Human-like face	Onboard camera and microphones, speech recognition and synthesis, eye contact, etc.	Language learning
Zenbo	Unspecified	Platform movement Turning left-right Displaying facial expressions, ete.	Teaching assistance
Maggie	Girl-like doll	Platform movement Moving head and eyelids Vocal utterances and mouth display, ete.	Edutainment
MIRO	Pet-like	Platform movement, moving cars, tail, eyelids, vocal utterances, etc.	Edutainment
Reeti	Cartoon-like	Expressive face	Storytelling

CommU	Humanoid	Human-like movement of the upper body Speaking, lip movement	Teaching assistance

Source: Reproduced from Youssef, K., Said, S., Al Kork, S. & Beyoutiy, T. (2023, p. 74).

These examples illustrate the wide range of social robots currently employed in educational contexts, each characterized by distinct technical capabilities and pedagogical affordances. Within the empirical part of this study, participants were introduced to the concept of social robots through the survey instrument (see Appendix C, Figure 10). To establish a shared understanding among respondents, representative examples of frequently used platforms were incorporated into the instrument, thereby providing clarity regarding both their appearance, linking abstract theoretical constructs to concrete, real-world instances. For definitional precision, the well-cited formulation by Bartneck and Forlizzi (2004) served as the conceptual foundation, defining a social robot as "an autonomous or semi-autonomous robot that interacts and communicates with humans by following socially expected behavioural norms" (adapted from Bartneck and Forlizzi, 2004). Having thus established both the conceptual foundations and the technological manifestations of social robots in education, the subsequent section examines how these robots are framed within higher education contexts.

2.2 Framing of Social Robots in Higher Education

2.2.1 Conceptual Background: What is Framing?

In sociology and communication studies, framing refers to the interpretive "frameworks" through which people make sense of events and technologies. Goffman's classic work on frame analysis describes a frame as a "schemata of interpretation" that enables individuals to "locate, perceive, identify, and label" occurrences in their environment. (Goffman, 1986, p. 21). In other words, frames highlight certain aspects of reality while filtering out others, thereby organizing experience and guiding action. Entman's oft-cited definition underscores that framing "essentially involves selection and salience. To frame is to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation" (Entman, 1993, p.52). In the context of educational technology, how a new tool is framed, for example, whether it is seen as a helpful innovation or a threatening intrusion, can significantly shape stakeholders' attitudes toward it and their willingness to adopt

it. Frames provide the context for "what this technology is and what it means for us," thereby influencing acceptance or resistance.

Applied to educational technology, framing determines how stakeholders interpret new tools and influences their attitudes toward adoption. Belpaeme et al., for example, reviewed dozens of classroom deployments of social robots and concluded that while robots often generate a strong initial engagement effect, this novelty may fade unless they are framed and integrated as helpful educational assistants (Belpaeme et al., 2018, pp. 2-3; 5-6). Johal similarly emphasises that when robots are positioned as interactive peers or companions, these framing fosters student engagement and increases willingness to interact with the technology (Johal, 2020, pp. 77-78). By contrast, van Ewijk et al. found that teachers often oscillate between assistant and threat frames, recognising potential benefits but at the same time voicing concerns about ethics, privacy, and the loss of human connection, concerns that ultimately influenced their readiness to adopt robots (van Ewijk et al., 2020, pp. 8-9). Taken together, these findings demonstrate that framing is not only a theoretical lens but also an empirically observable factor shaping the adoption of social robots in education.

2.2.2 Framing of Social Robots in Education

Building on the conceptual foundations outlined in Section 2.2.1, this section examines how social robots are specifically framed in educational contexts. To address the first part of the research question: "How do students and academic staff in German higher education frame the integration of social robots (see Section 1.4) - this thesis draws on recent literature (2020-2025) to identify common interpretive frames.

Robot as Assistant

Belpaeme et al. emphasise that "as a tutor or teacher, robots provide direct curriculum support through hints, tutorials, and supervision" (Belpaeme et al., 2018, p. 5). In this assistant frame, robots are positioned as instructional aides that can handle routine or structured tasks, deliver feedback, and support teachers in focusing on more personalised and complex aspects of instruction. Donnermann et al. conducted a long-term field study in higher education where a social robot acted as an adaptive tutor, supporting students' exam preparation, sustaining motivation, and ultimately contributing to improved learning outcomes compared to students who did not interact with the robot (Donnermann et al., 2022, pp. 3-5). Johal similarly emphasised that social robots can redirect students' attention and enhance engagement when employed as interactive aids in learning activities (Johal, 2020, pp. 77-78). This assistant frame highlights the robot's utility and compatibility with educational needs, portraying it as a

supportive tool that augments teaching and learning rather than threatening the role of human educators.

Robot as Innovation (Symbol of Progress)

Aoun argued that the rise of robotics and AI is pushing higher education to develop "robot-proof" curricula, framing robots as catalysts of educational reform and institutional innovation (Aoun, 2017, pp. 13-15). Building on this perspective, Lehmann and Svarny (2021) reported on an empirical study in which the social robot Pepper was introduced during university lectures to provide different types of feedback. They describe the deployment not only as a functional aid but also as an innovative step in higher education, signalling the potential of robots to transform teaching practices and embodying universities' search for digital progress (Lehmann & Svarny, 2021, p. 284). Similarly, Holmes, Fadel, and Bialik (2019) emphasise that the adoption of AI and robotics in education is often framed as a breakthrough, representing a marker of institutional modernisation and competitiveness (Holmes, Fadel & Bialik, 2019, p. 11). Within this innovation frame, robots are therefore associated less with immediate pedagogical outcomes and more with the symbolic value of progress, transformation, and being positioned at the forefront of digitalisation in higher education.

Robot as Companion

Belpaeme et al. note that "robots can also be peers or learning companions for humans" (Belpaeme et al., 2018, p. 6), emphasising that such peer-to-peer interactions may be less intimidating than traditional tutor-student settings and can foster sustained engagement. Johal (2020, pp. 77-78) likewise emphasised that social robots can be perceived as companions or peers, engaging students socially and emotionally, and thereby enhancing motivation and willingness to learn. Van Van Ewijk et al. reported that teachers observed how children "are reported to project friendship or attachment onto social robots," drawing parallels between a humanoid robot such as NAO and the way a toddler might see a teddy bear as a living friend (van Ewijk et al., 2020, p. 4). This companion frame thus portrays robots not merely as instructional tools but as social entities capable of fostering rapport, trust, and enjoyment, while simultaneously raising questions about the risks of excessive attachment in educational contexts.

Robot as Threat

Van Ewijk et al. documented that educators frequently expressed reservations, framing robots as potential threats to pedagogy and human interaction. In focus group discussions, teachers highlighted concerns about privacy and ethics, noting "the possibility of extensive data

collection, like face and voice recognition, and the robot being disruptive in the classroom." They further warned that robots "might not see the consequences of their actions, or the children [might become] 'mechanical' because of the loss of human contact" (van Ewijk et al., 2020, p. 1). Consistent with this, a large-scale survey identified a "Sceptic" cluster who regarded social robots' capacity for social interaction and bonding with children as "potentially dangerous," expressed worries about IT security and the stability of accountability systems, insisted that robots be trustworthy and not pass on children's secrets, and viewed sharing robot-collected data with third parties as problematic (Smakman et al., 2021, p. 13). Beyond privacy and safety, some authors warn of the risk of replacement: robots may take over routine educational tasks, potentially diminishing the teacher's role. While some scholars argue that robots could relieve teachers from repetitive duties without ever replacing them entirely, others caution that any displacement of authentic human interaction in education should be critically scrutinised (Torras, 2023, p. 7). This debate on substitution itself forms part of the threat frame, reflecting broader anxieties about technological encroachment into human domains.

Robot as Gimmick

Rasmussen et al. (2024) highlight how robots in hospital environments are often caught between being viewed as a "new colleague" or dismissed as a "gimmick hurdle" (Rasmussen et al., 2024). In their user-centric scoping review, health professionals noted that robots were sometimes perceived as superficial novelties, especially when their utilitarian value was limited (Rasmussen et al., 2024). In such cases, staff questioned whether the machines added genuine functional support or merely distracted from core medical tasks. The very framing of the study, posing the dilemma "new colleague or gimmick," underscores this tension: robots can either be recognized as meaningful contributors or criticized as decorative tricks with little real-world impact (Rasmussen et al., 2024).

Similar concerns arise in the service context. A study on human-robot service interaction found that users frequently oscillated between evaluating robots as an "improvement" or a "gimmick" depending on perceived value (Hu, 2021). When robots demonstrated clear instrumental utility, participants were more inclined to regard them positively (ResearchGate, 2021). Conversely, when utility was low, hedonic features, such as entertainment or aesthetic appeal, dominated user perceptions, leading many to label robots as gimmicks rather than serious innovations (Hu, 2021). This ambivalence illustrates that social acceptance hinges not only on technical performance but also on whether robots are seen as adding substantive value beyond novelty (Hu, 2021).

Together, these studies reveal a consistent pattern: robots risk being trivialized as gimmicks when their contributions are overshadowed by perceptions of superficiality or entertainment. The "gimmick frame" thus encapsulates skepticism toward robots that fail to demonstrate clear, durable benefits, reinforcing doubts about their legitimacy in professional and service domains (Rasmussen et al., 2024; Hu, 2021).

In summary, the literature reveals five recurrent interpretive frames: Assistant, Innovation, Companion, Threat, and Gimmick, which consistently shape perceptions of social robots in educational contexts. While these frames have predominantly been identified in international studies, the present thesis focuses specifically on the German higher education context. In order to empirically assess the salience of these frames among students and staff in German universities, the following section translates them into measurable survey items.

2.2.3 Operationalization of Frames for the Survey

Building directly on the frames identified in Section 2.2.2, the present section operationalises them for empirical testing. To empirically test these interpretive frames in the German higher education context, they were translated into concrete questionnaire items. Based on the literature review, five frames were identified: Assistant, Innovation, Companion, Threat, and Gimmick, and for each frame a representative statement was formulated. These statements were integrated into the SoSci Survey instrument (see Appendix C, Figure 14).

The final wording of the items is as follows:

- A social robot can function as a helpful teaching assistant for instructors in higher education. (Assistant frame)
- Using social robots in the classroom demonstrates that a university is innovative. (Innovation frame)
- I am worried that social robots could replace human educators. (Threat frame)
- Interacting with a social robot can make learning more engaging by giving students a feeling of having a friendly companion in class. (Companion frame)
- Social robots in higher education are more of a novelty or marketing gimmick than a truly useful tool. (Gimmick frame)

These are self-formulated statements, derived directly from the theoretical frames discussed in Section 2.2.2 Framing of Social Robots in Education. They are measured on a five-point Likert scale (from strongly disagree to strongly agree), with an additional don't know option.

By operationalising the frames in this way, the survey enables a systematic assessment of which interpretive patterns are most salient among students and staff in German higher education. The

responses provide the empirical basis for addressing the first part of the research question: "How do students and academic staff in German higher education frame the integration of social robots…?" (see Section 1.4). At the same time, framing theory also provides the conceptual foundation for addressing the second part of the research question: "…what impact do these frames have on their acceptance of the technology?" (see Section 1.4) - by linking the identified interpretive patterns to adoption intention, thereby serving as the theoretical basis for the formulation of Hypothesis 1 (see Section 2.4).

While framing highlights how social robots are interpreted and discussed, it does not fully explain why certain technologies are adopted more readily than others. To capture these adoption dynamics more comprehensively, the following chapter turns to Rogers' Diffusion of Innovations theory and subsequent perception models. These perspectives complement the framing approach by focusing on the attributes of innovations that influence acceptance and thus provide an additional theoretical lens for understanding adoption processes in higher education.

2.3 Diffusion of Innovations and Perception Factors

2.3.1 Rogers' Diffusion of Innovations Theory

Rogers' Diffusion of Innovations theory provides a foundational framework for understanding how new ideas and technologies spread within a social system, and it has been widely applied in studies of innovation adoption in higher education settings (Sahin, 2006, p. 14). Rogers defines "diffusion" as the process by which an innovation, an idea, practice, or object perceived as new is communicated through certain channels over time among members of a social system (Rogers, 2003, p. 31). This definition highlights four fundamental elements in any diffusion process: the innovation itself, the communication channels, time, and the social system (Rogers, 2003, p. 36). Diffusion is not only a technical matter but very much a social process: it relies on human interactions and communication networks through which information about the innovation flows (Rogers, 2003, p. 22). In the context of a university, for example, the social system includes faculty, students, and administrators, and diffusion occurs via both formal channels (such as departmental committees, workshops or pilot programs) and informal peer networks. Rogers' model has been deemed highly appropriate for examining how faculty and institutions adopt new technologies or practices in higher education, offering insight into why some innovations achieve broad uptake while others struggle to gain traction (Sahin, 2006, p. 14).

A key insight of Rogers' theory is that adopters of an innovation can be categorised according to the timing of their adoption relative to others (see Figure 1), with the overall process typically following an S-shaped curve that moves from a small group of early users toward mainstream acceptance (Rogers, 2003, p.48).

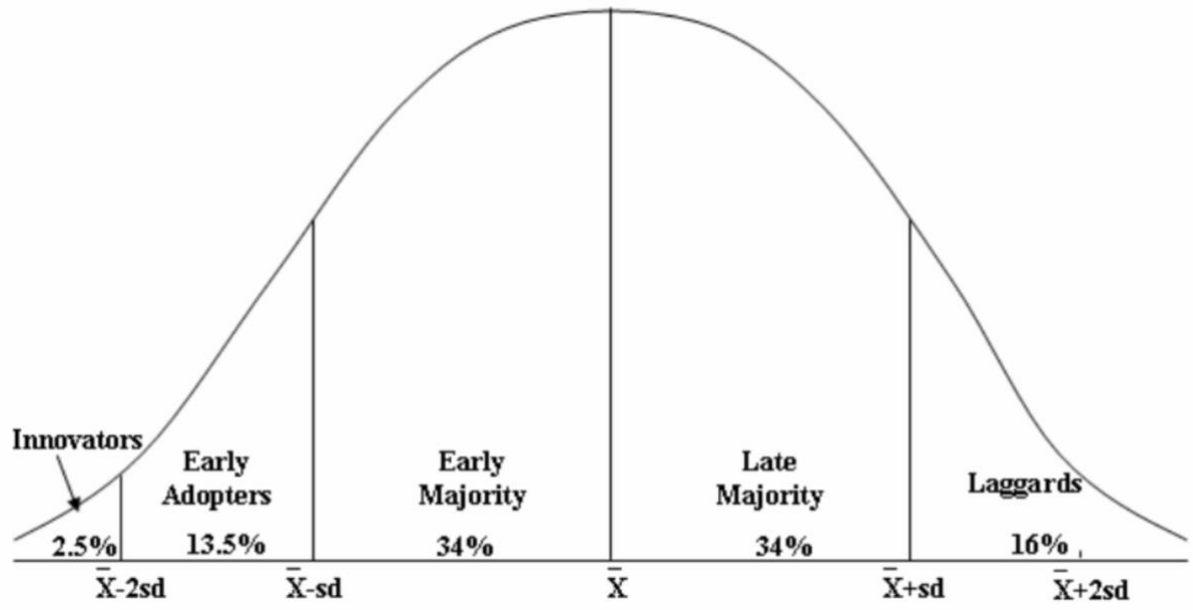


Figure 1 Adopter Categorization on the Basis of Innovativeness

Source: Diffusion of Innovations, fifth edition by Everett M. Rogers, p. 306. Copyright (c) 2003 by The Free Press. Reprinted with permission of the Free Press: A Division of Simon & Schuster.

Rogers distinguishes five adopter categories along a roughly bell-shaped adoption distribution: "innovators", the venturesome first ~2.5% of individuals to adopt; "early adopters", the next ~13.5% who are typically respected opinion leaders; the "early majority" (next ~34%), who adopt after a varying degree of deliberation; the "late majority"(~34%), who are more skeptical and wait until most others have adopted; and "laggards" (the final ~16%), who are the most hesitant and traditional in outlook (Rogers, 2003, pp. 305-306). Each group plays a different role in the diffusion process. Innovators are willing to take risks on new ideas and often have access to outside networks and resources (Rogers, 2003, p. 308). Early adopters tend to be more integrated within the local social system and often hold formal or informal leadership positions that enable them to influence others (Rogers, 2003, p. 309). Indeed, Rogers notes that early adopters serve as role models for others, their endorsement of an innovation effectively puts a "stamp of approval" on the new idea, reducing uncertainty for the early majority who may be waiting for evidence of the innovation's value (Rogers, 2003, p. 309). In contrast, the late

majority and laggards are more cautious; they typically adopt an innovation only when it has become well established or due to necessity or external pressure, and they often require substantial assurance and support before changing longstanding practices (Rogers, 2003, p. 310). This staged adoption pattern means that the rate of diffusion in a given environment is strongly influenced by the social dynamics among these groups, for example, the presence of credible early adopters and effective communication of results can spur faster uptake, whereas a lack of trusted champions can slow the spread of a new practice.

Empirical evidence from higher education underscores the relevance of Rogers' model. For instance, a multi-university study in Germany examined the rollout of a new campus-wide technology service (a cloud storage innovation) and found that diffusion patterns aligned with Rogers' theory (Rudolph, Vogl, Angenent, Thoring, Wilmer & Schild, 2016, pp. 5-6). In that study, institutions with a higher proportion of enthusiastic early adopters (i.e. technologically "innovative" faculty and students) achieved more rapid initial uptake of the service, and adoption was further accelerated by active promotion and communication efforts to raise awareness (Rudolph et al., 2016, pp. 5-6). By contrast, simply the size of the university did not significantly affect adoption speed; what mattered more was having a critical mass of innovators/early adopters and effective communication channels, consistent with Rogers' emphasis on the social structure of the diffusion process (Rogers, 2003, pp. 247-248; Rudolph et al., 2016, pp. 5-6). These findings illustrate how, even in the context of German universities with their particular organizational cultures, the diffusion of an innovation depends on engaging early champions and leveraging communication networks to influence the broader community.

In addition to social dynamics and adopter categories, Rogers highlighted that the characteristics of the innovation itself can profoundly influence its adoption. In fact, Rogers identified five key perceived attributes of an innovation, relative advantage, compatibility, complexity, trialability, and observability, which shape potential adopters' decisions and largely determine the innovation's rate of adoption (Rogers, 2003, pp. 41-42). Research shows that these five attributes, as perceived by users, can explain between about 49% and 87% of the variance in adoption rates observed across different innovations (Rogers, 2003, pp. 246-247). In other words, how faculty or institutions perceive an innovation's advantages, its alignment with existing values/practices, its difficulty, the ability to experiment with it, and the visibility of its results will heavily influence how quickly it spreads on campus. Thus, Rogers' diffusion theory not only accounts for who adopts innovations and through what social mechanisms, but also for what features of the innovation encourage or hinder its uptake. The following section

(2.2.2) will examine these innovation attributes in detail and discuss how each attribute can impact the adoption of new educational innovations in the higher education context.

2.3.2 Perception Model of Moore & Benbasat (1991)

Rogers' diffusion model explains adoption both through the categorisation of users into innovators, early adopters, the majority, and laggards (Rogers, 2003, pp. 305-306), as well as through five perceived attributes of innovations: relative advantage, compatibility, complexity, trialability, and observability, hat shape adoption decisions (Rogers, 2003, pp. 41-42) (see Section 2.3.1). Building on this foundation, Moore and Benbasat (1991) refined these attributes to better capture user perceptions in the context of information technology.

Moore and Benbasat's model includes the original five attributes from Rogers decisions (Rogers, 2003, pp. 41-42) (see Section 2.3.1), relative advantage, compatibility, complexity (reframed as ease of use), trialability, and observability, and adds three additional constructs: image, voluntariness of use, and visibility (Moore and Benbasat, 1991, p. 195). This expanded model was developed through empirical research involving computer technology and has since been widely applied in educational and organisational IT adoption studies (Straub, 2009, p. 637).

2.3.3 Operationalization of Innovation Attributes for the Survey

While Section 2.2 focused on the interpretive frames through which social robots are understood, the present section turns to adoption-related perception models that explain why such technologies are embraced or resisted. In this way, framing theory (Section 2.2) and innovation adoption theory (Section 2.3) complement each other, together forming the analytical lens of this study.

The integration of Rogers' (2003) Diffusion of Innovations theory and the extended perception model developed by Moore and Benbasat (1991) provides a robust theoretical foundation for analysing the acceptance of social robots in higher education. Both frameworks are well established in the literature and have been successfully applied to the adoption of various digital innovations, particularly within educational and organisational contexts.

Social robots represent a complex and multifaceted innovation that combines elements of automation, artificial intelligence, and interpersonal interaction. As such, their adoption in educational institutions cannot be adequately captured by technical specifications alone. Instead, it requires a deep understanding of how potential users perceive the innovation's attributes, how it aligns with their values and practices, and how their interpretive frames shape

their openness to integration. The dual-framework approach adopted in this study allows for such a nuanced analysis.

Rogers' five innovation attributes: relative advantage, compatibility, complexity (ease of use), trialability, and observability, have proven to be consistent predictors of adoption across domains. These attributes are particularly pertinent in the context of higher education, where innovations must navigate institutional inertia, pedagogical norms, and a diverse user base. By measuring these attributes through survey items, this study captures how stakeholders evaluate social robots in relation to their academic practices and expectations. For instance, a robot perceived as offering clear improvements in teaching effectiveness (relative advantage), aligning with instructional goals (compatibility), and being easy to test or observe (trialability and observability) is more likely to be adopted.

Moore and Benbasat's (1991) model enhances the analytical depth by introducing refined perception variables such as result Observability, voluntariness of use, image, and visibility. These dimensions allow for assessing not only whether an innovation is seen as beneficial, but also whether its benefits are evident, whether its use feels voluntary or imposed, and how it is positioned within the institutional environment. In status-conscious academic settings, symbolic aspects such as image and visibility are highly relevant for explaining adoption patterns.

To operationalize these theoretical constructs, the following items were included in the SoSci Survey instrument (see Appendix C, Figure 13). The final wording of the items is as follows:

Relative Advantage: *"Using a social robot would improve the quality of teaching."*

Compatibility: *"A social robot fits well with my teaching/learning style."*

Ease of Use (Complexity): *"The functions of a social robot are easy to understand and use."*

Trialability: *"I believe I would have the chance to try a social robot at my university."*

Observability: *"The outcomes of using a social robot in education are easy to observe and explain."*

Image: *"Using a social robot would improve how others perceive me as a progressive educator/student."*

Visibility: *"The presence of a social robot in education attracts attention and interest."*

Voluntariness of Use: *"I would prefer to have the freedom to choose whether or not to use a social robot in my work/study."*

In sum, this integrated operationalisation provides the empirical basis for testing the second part of the research question (…what impact do these frames have on acceptance?), regarding

the impact of perceptions on the acceptance of social robots. It also supports the formulation of Hypotheses 2 and 3 (see Section 2.4), ensuring that the study moves beyond descriptive observation toward a theoretically grounded and measurable analysis of adoption conditions in German higher education.

2.4 Derivation and Formulation of Hypotheses

In social research, hypotheses are formulated as testable expectations derived from theoretical propositions. According to Babbie (2013, p. 70), a hypothesis is "a specified testable expectation about empirical reality that follows from a more general proposition." In line with this understanding, the following hypotheses are derived from the theoretical frameworks outlined in Sections 2.2 and 2.3.

H1: Framing and Intention to Adopt

As outlined in **Section 2.2 (Framing Theory)**, the way technologies are framed influences how individuals interpret their meaning and relevance. According to Goffman's (1986) concept of frames and Entman's (1993) notion of selective emphasis, framing highlights certain aspects of a phenomenon while filtering out others, thereby shaping interpretation and guiding action (*see Section 2.2.1; Goffman, 1986, p. 21; Entman, 1993, p. 52*).

Applied to social robots in higher education, **positive frames** highlight supportive and progressive functions. The *Assistant* frame emphasizes the robot's role as an instructional aide, providing curriculum support and feedback, thereby aligning with educational needs (Belpaeme et al., 2018, pp. 2-6; Donnermann et al., 2022, pp. 3-5; Johal, 2020, pp. 77-78; *see Section 2.2.2*). The *Innovation* frame positions robots as symbols of progress and institutional modernisation, associating their adoption with competitiveness and digital transformation (Aoun, 2017, pp. 13-15; Lehmann & Svarny, 2021, p. 284; Holmes, Fadel & Bialik, 2019, p. 11; *see Section 2.2.2*). The *Companion* frame emphasizes their role as peers or social partners, capable of fostering trust, motivation, and emotional engagement (Belpaeme et al., 2018, p. 6; Johal, 2020, pp. 77-78; van Ewijk et al., 2020, p. 4; *see Section 2.2.2*).

Based on these insights, the assumption is formulated that such positive framings may increase stakeholders' willingness to adopt social robots in higher education, which will be tested empirically in the survey.

In contrast, **negative frames** stress doubts or risks. The *Threat* frame highlights concerns about ethics, privacy, and the loss of human interaction, as well as fears of substitution (van Ewijk et al., 2020, p. 1; Smakman et al., 2021, p. 13; Torras, 2023, p. 7; *see Section 2.2.2*). The *Gimmick* frame, by contrast, depicts robots as superficial novelties that lack substantive

value, raising skepticism about their legitimacy (Rasmussen et al., 2024; Hu, 2021; *see Section 2.2.2*).

Accordingly, the assumption is that such negative framings may reduce stakeholders' willingness to adopt social robots, which will likewise be addressed in the empirical study.

General Hypothesis 1 (H1): ***Framing significantly influences the intention to adopt social robots in higher education, with positive frames increasing and negative frames decreasing adoption intention.***

H1a: *An Assistant frame is positively associated with the intention to adopt.*

H1b: *An Innovation frame is positively associated with the intention to adopt.*

H1c: *A Companion frame is positively associated with the intention to adopt.*

H1d: *A Gimmick frame is negatively associated with the intention to adopt.*

H1e: *A Threat frame is negatively associated with the intention to adopt.*

H2: Innovation Attributes and Intention to Adopt

The second set of hypotheses is grounded in **Section 2.3 (Diffusion of Innovations and Perception Models)**. Rogers (2003) identified five core attributes: *relative advantage, compatibility, complexity/ease of use, trialability,* and *observability*, that determine adoption rates (*see Section 2.3.1; Rogers, 2003, pp. 15-16*). These attributes reduce uncertainty by clarifying benefits and usability, thereby shaping adoption decisions. Moore and Benbasat's (1991) extended perception model, also discussed in **Section 2.3.3**, adds *image, voluntariness,* and *visibility* as adoption-relevant constructs, especially in organizational contexts.

Taken together, these models suggest that favorable perceptions of innovation attributes should foster stronger adoption intentions in higher education. On this theoretical basis, the assumption is formulated that positive perceptions of innovation attributes increase stakeholders' willingness to adopt social robots, which will be examined in the empirical study.

General Hypothesis 2 (H2): ***Positive perceptions of innovation attributes are positively associated with the intention to adopt social robots in higher education.***

H2a: *Relative advantage is positively associated with the intention to adopt.*

H2b: *Compatibility is positively associated with the intention to adopt.*

H2c: *Ease of use is positively associated with the intention to adopt.*

H2d: *Trialability is positively associated with the intention to adopt.*

H2e: *Observability is positively associated with the intention to adopt.*

H2f: *Image is positively associated with the intention to adopt.*

H2g: *Voluntariness is positively associated with the intention to adopt.*

H2h: *Visibility is positively associated with the intention to adopt.*

H3: Experience and Intention to Adopt

The third hypothesis builds on insights from **Section 2.3 (Diffusion of Innovations)**, particularly the attribute of *trialability*. Rogers (2003) emphasized that opportunities to try out an innovation reduce uncertainty and accelerate adoption (*see Section 2.3.2; Rogers, 2003, p. 16*). In the context of this study, prior personal interaction with a social robot can be understood as a concrete form of trialability, as it provides direct exposure to the technology. Such interaction may reduce anxiety, foster familiarity, and strengthen trust in the robot's potential value. As outlined in **Section 2.3.4**, experiential familiarity represents an important determinant of adoption decisions.

Accordingly, the assumption is formulated that respondents with previous interaction experience at their university will express higher adoption intentions than those without such experience, which will be tested empirically in the survey.

Hypothesis 3 (H3): ***Individuals with prior experience with social robots demonstrate a higher intention to adopt than those without prior experience.***

In summary, Chapter 2 established the theoretical framework of this study by outlining the key concepts of framing and innovation adoption, and by deriving hypotheses that connect these theoretical perspectives to the adoption of social robots in higher education. The formulated hypotheses (H1-H3) provide a structured basis for empirical examination, linking interpretive frames, perceived innovation attributes, and prior experience to adoption intention. Building on this foundation, the next chapter presents the methodological design of the study, explaining how the theoretical constructs are operationalized into measurable variables and tested through a quantitative survey approach.

3 Methodology and Research Design

3.1 Justification of Method and Research Approach

This thesis applies an empirical and quantitative research approach. A quantitative design is chosen because the aim is to test hypotheses derived from the theoretical framework (see Section 2.2; Section 2.3; Section 2.4) and to provide statistically reliable evidence on the adoption of social robots in higher education. Following Babbie (2020), this process involves a transformation from abstract theoretical constructs to measurable variables. In other words, the study first clarifies what is meant by concepts such as "frames" or "innovation attributes" (conceptualization), and then translates them into concrete survey items and indicators that can be analysed statistically (operationalization) (Babbie, 2020, pp. 169–177, esp. p. 174).

An empirical design is appropriate because the study investigates observable attitudes and perceptions of the main target groups, namely students and academic staff. Social research is based on examining real-world phenomena and formulating hypotheses that can be tested (Babbie, 2013, pp. 4–6, 70). To gather primary data, a structured online survey (SoSci Survey) is used. The standardised wording and scaling of items ensure that responses are comparable across participants (Babbie, 2013, pp. 177–186, 187–193, 229–237). This design also allows for the application of statistical methods such as correlation analyses, regression models, and group comparisons to test the proposed hypotheses (Babbie, 2013, pp. 413–437, 459–496; see Section 4).

The methodological approach is further justified by the nature and scope of the research problem. The **market and policy context** demonstrates growing practical relevance of educational/social robotics (*see Section 1.1; Grand View Research, 2024a; 2024b; Statzon, 2024; Robotics Institute Germany, n.d.; Lu et al., 2025*), while prior academic work highlights meaningful **pedagogical effects** and user engagement (*see Section 1.1; Section 2.1.3; Belpaeme et al., 2018; Johal, 2020; Donnermann et al., 2020; Zamora et al., 2025; Baena-Rojas et al., 2025*). Investigating the relationships between **frames**, **perceived attributes**, and **intention to adopt** therefore requires quantifiable indicators and inferential testing. A purely qualitative design would not permit equivalent hypothesis testing or the identification of statistically significant relationships between variables. Consequently, a **quantitative survey** represents the most suitable method for answering the research question and for generating empirical evidence to support or reject the proposed hypotheses (*see Section 1.4; Section 2.4*).

This study addresses the following central research question: *How do students and academic staff in German higher education frame the integration of social robots, and what impact do these frames have on their acceptance of the technology?* (*see Section 1.4*).

To address the first part of the RQ (How do students and academic staff frame the integration of social robots?), the thesis identifies five recurrent interpretive frames from recent literature: Assistant, Innovation, Companion, Threat, and Gimmick, and operationalises them as survey items (see Section 2.2.2). The item pool is derived from the theoretical discussion and empirical evidence on framing in educational robotics (e.g., Assistant/Companion: Belpaeme et al., 2018; Johal, 2020; Donnermann et al., 2022; Innovation: Aoun, 2017; Lehmann & Svarny, 2021; Holmes, Fadel & Bialik, 2019; Threat: van Ewijk et al., 2020; Smakman et al., 2021; Torras, 2023; Gimmick: Rasmussen et al., 2024; Hu, 2021) and translated into Likert-type statements implemented in SoSci Survey, which follow the widely applied Likert scaling technique for measuring attitudes in survey research (Babbie, 2013, p. 217).

In this study, the Likert scaling technique is applied in its widely used response format, allowing respondents to express the intensity of their agreement with a series of statements. Each construct, such as interpretive frames (Assistant, Innovation, Companion, Threat, Gimmick), innovation attributes (relative advantage, compatibility, ease of use, trialability, observability, image, voluntariness, visibility), and adoption intention, is operationalszed into multiple items formulated as declarative statements. Respondents evaluate these statements on a five-point Likert scale ranging from *strongly disagree* to *strongly agree*, with an additional *don't know* option to reduce forced responses (see Appendix C).

This design follows the theoretical logic of Likert scaling, which captures not only the direction (agreement vs. disagreement) but also the relative strength of attitudes, thereby ensuring ordinal measurement of perceptions (Babbie, 2013, pp. 217-219). By summing or averaging across multiple items within each construct, composite indices can be created that reflect the underlying latent variables. For example, agreement with statements such as *"Using social robots in the classroom demonstrates that a university is innovative"* or *"I am worried that social robots could replace human educators"* operationalizes the Innovation and Threat frames, respectively. Similarly, items measuring adoption intention (e.g., *"I would support the introduction of a social robot in my university"*) provide a direct empirical indicator of behavioural readiness.

Thus, the questionnaire structure directly reflects the theoretical principles of Likert scaling: it ensures comparability across respondents, minimizes ambiguity, and allows for the creation of reliable indices that can be tested against the hypotheses.

To address the second part of the research question (…what impact do these frames have on acceptance?), the empirical design tests hypotheses derived from the theoretical frameworks on framing and innovation adoption (see Section 2.4). For this purpose, the study likewise applies the Likert scaling technique, using multiple statements to capture respondents' levels of agreement with adoption-related constructs. Three hypothesis blocks structure the analysis.

The first block, H1: Framing and Intention to Adopt, examines whether positive frames (Assistant, Innovation, Companion) are positively associated with intention to adopt, and whether negative frames (Threat, Gimmick) are negatively associated (see Section 2.2.2). The corresponding sub-hypotheses specify that H1a Assistant (+), H1b Innovation (+), H1c Companion (+), H1d Gimmick (-), and H1e Threat (-).

The second block, H2: Innovation Attributes and Intention to Adopt, builds on Rogers' Diffusion of Innovations (relative advantage, compatibility, ease of use, trialability, observability; see Section 2.3.2) and the Moore and Benbasat (1991) perception model (image, voluntariness, visibility, observability; see Section 2.3.3). The hypotheses test whether favorable perceptions of these attributes increase adoption intention. The sub-hypotheses specify that H2a Relative advantage (+), H2b Compatibility (+), H2c Ease of use (+), H2d Trialability (+), H2e Observability (+), H2f Image (+), H2g Voluntariness (+), and H2h Visibility (+).

The third block, H3: Experience and Intention to Adopt, links trialability to prior personal interaction with social robots in the university context, treating prior experience as a concrete form of trialability that reduces uncertainty and fosters adoption readiness (Section 2.4).

This two-step empirical design, consisting of the derivation and operationalisation of frames and adoption attributes from the theory, and the subsequent hypothesis testing using standard statistical procedures, ensures that both dimensions of the research question are examined in a theoretically grounded and methodologically consistent manner.

3.2 Description of the Quantitative Survey

For the purpose of this study, a standardized online questionnaire was developed and implemented via the survey platform SoSci Survey. The questionnaire was designed to ensure comparability and reproducibility of responses by using fixed wording, predefined answer categories, and a consistent sequence of questions (Babbie, 2013, p. 217). In line with Babbie's

(2013) recommendations on questionnaire construction, particular attention was paid to the ordering of items, as the sequence in which questions are presented can influence how respondents interpret and answer subsequent items. To minimise such order or context effects, the thematic blocks were arranged deliberately: items on innovation attributes were presented prior to framing-related items. This design choice was made to prevent respondents from being primed by explicit interpretive labels such as “Assistant,” “Innovation,” or “Threat” too early in the survey. In doing so, the study reduces the risk of biased evaluations and ensures that responses to innovation attributes remain as independent and unbiased as possible, thereby enhancing the validity of the collected data. In total, the survey consisted of ten sections with closed-ended questions and one introductory and concluding page.

The survey began with an introduction page informing participants about the purpose of the study, the estimated time required (approximately five minutes), the voluntary and anonymous nature of participation, and the confidentiality of responses. This introduction aimed to increase transparency and trust, thereby reducing the risk of non-response (see Appendix C, Figure 4).

After the introduction, participants were asked several socio-demographic and background questions. These included their current role at the institution (student, lecturer, researcher, or administrative staff), their field of study or teaching, and their age group (see Appendix C, Figure 5, Figure 6). Additionally, participants were asked to indicate their prior experience with selected digital technologies (e.g., learning platforms, artificial intelligence tools such as ChatGPT, social robots, or virtual/augmented reality). These questions served both as descriptive sample characteristics and as independent variables for Hypothesis 3 (see Appendix C, Figure 7).

Subsequently, participants were presented with a standardized definition of social robots, including examples (Pepper, NAO, Cue). To ensure a consistent understanding of the research object, participants were provided with a standardized definition of social robots: “A social robot is an autonomous or semi-autonomous robot that interacts and communicates with humans in ways that follow socially expected behavioural norms” (adapted from Bartneck & Forlizzi, 2004). This definition was presented alongside visual examples (e.g., Pepper, NAO, Cue) in order to minimize interpretive variance and to create a shared frame of reference for all respondents (see Appendix C, Figure 9).

The main part of the questionnaire consisted of three thematic blocks, which directly correspond to the hypotheses of this study. The first block measured the intention to adopt social robots in higher education, based on three items (support of introduction, personal usage intention,

recommendation to peers). These items were averaged into a composite variable (MeanInt) and serve as the dependent variable for Hypotheses 1-3 (see Appendix C, Figure 11).

The second block captured **perceived innovation attributes**, drawing on Rogers' Diffusion of Innovations framework and the perception model by Moore & Benbasat. Items measured constructs such as relative advantage, compatibility, ease of use, trialability, observability, image, voluntariness, and visibility. These variables were operationalized to test Hypothesis 2, which assumes that higher scores on these attributes are positively associated with adoption intention (see Appendix C, Figure 12).

The third block addressed **framing effects**, by presenting statements that reflect positive frames (e.g., "A social robot can function as a helpful teaching assistant" / "Using social robots demonstrates that a university is innovative") and negative frames (e.g., "I am worried that social robots could replace human educators" / "Social robots are more of a marketing gimmick than a useful tool"). These measures operationalize Hypothesis 1, which investigates the relationship between framing and adoption intention (see Appendix C, Figure 13).

All constructs in the main part of the survey were measured using a standardized five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). The use of Likert scales is well established in social science research for capturing subjective evaluations and attitudes (Babbie, 2013, p. 217).

The survey concluded with a short thank-you page, including an optional SurveyCircle code for participants who wished to receive recognition for their contribution. This closing ensured a polite and motivating end to the questionnaire and encouraged participation in similar research projects (see Appendix 13).

3.3 Data Preparation and Processing

3.3.1 Exporting and cleaning the raw data from SoSci Survey/SPSS

The raw data for this study were collected using the SoSci Survey platform and subsequently exported for statistical analysis. The export was conducted in the SPSS format via the syntax file option, which ensures compatibility with IBM SPSS Statistics and allows the automatic assignment of variable and value labels. This procedure is particularly useful for survey research, as it reduces the risk of errors when transferring metadata such as response codes, missing value definitions, and item texts (Field, 2018, p.273).

In order to ensure the quality and reliability of the dataset, several cleaning steps were performed before starting the empirical analysis. First, incomplete interviews and pretest responses were excluded from the dataset. Following the export criteria defined in SoSci

Survey, only respondents who reached the final page of the questionnaire were retained. As a result, the final dataset consisted of **N = 157 valid cases**, which formed the empirical basis of the statistical tests.

Second, all missing values defined by the survey system (e.g., -9 = *not answered*, -8 = *don't know*) were recoded and declared as missing values in SPSS. This step is crucial to prevent biased parameter estimates, as treating missing values as valid responses would distort descriptive statistics and inferential tests (Field, 2018, p.261). Through these procedures, the raw data were transformed into a clean and analysis-ready dataset.

3.3.2 Coding of variables

The dataset exported from SoSci Survey initially contained long, automatically generated variable names based on the full wording of survey items. To simplify statistical analysis in SPSS and improve clarity, all variables were recoded into shorter, intuitive labels that reflect the underlying constructs. In quantitative research, variables are typically classified as independent (predictors) and dependent (outcomes) (Field, 2018, pp. 48–50). In this study, framing constructs and innovation attributes serve as independent variables, while "Intention to Adopt" is treated as the dependent variable. This distinction forms the basis for regression analyses and hypothesis testing.

For example, the original variable names imported from SoSci Survey corresponded to the full text of the survey items, such as *F101_01*: "Framing: A social robot can function as a helpful teaching assistant for instructors in higher education." (see Appendix A). Such lengthy names were not only impractical for regression analysis and correlation tables but also increased the risk of errors in reporting results. Therefore, all variables were recoded into concise but meaningful identifiers that directly reference the respective construct (see Appendix A).

In addition, a composite variable (*MeanInt*) was computed as the mean score across the three items measuring adoption intention (*Intention_Support, Intention_Use, Intention_Recommend*). This aggregation reflects the overall construct of "Intention to Adopt" and ensures a reliable measure for subsequent hypothesis testing. By applying this systematic coding, the dataset was standardized and structured.

3.4 Preliminary Checks

3.4.1 Descriptive statistics of the sample

In total, **N = 157 valid cases** were included in the analysis after data cleaning. The descriptive statistics of the sample provide an overview of the demographic composition of the respondents,

including their current role at the institution, field of study or teaching, age distribution, and prior interaction experience with social robots.

With regard to the **current role** at the institution, the distribution shown in Table 2 indicates that the sample is strongly dominated by students (**97.5%**, n = 153). Only a very small proportion of respondents identified themselves as professors/lecturers (**1.3%**, n = 2) or research staff (**1.3%**, n = 2). This indicates that the perceptions reflected in the survey largely stem from the student population, while academic staff are underrepresented.

Table 2 Current Role of Respondents at the Institution

CurrentRole

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Student	153	97.5	97.5	97.5
	Professor / Lecturer	2	1.3	1.3	98.7
	Research staff	2	1.3	1.3	100.0
	Total	157	100.0	100.0	

Source: Own survey data, analysis with IBM SPSS Statistics

In terms of the field of study, the distribution shows a diverse spread across disciplines, although certain areas are more strongly represented. The largest groups were students from Business, Management, and Marketing (21.0%), Economics (17.8%), and the Social Sciences (17.2%) (see Appendix F, Table 13).

The age distribution confirms the dominance of younger respondents. More than half of the participants were under 24 years old (56.1%), while an additional third fell into the 25-34 age group (33.1%). The older age brackets were represented only marginally: 35-44 years (8.3%) and 45-54 years (2.5%) (see Appendix F, Table 14). These findings are consistent with the high proportion of students in the sample.

Finally, regarding prior interaction with social robots, only 24.2% of respondents indicated that they had direct experience with social robots in an educational setting (e.g., Pepper or NAO), whereas the majority (75.8%) reported no such experience (see Appendix F, Table 15). This outcome is not unexpected, as social robots are still a relatively new technology in higher education and have only been introduced in selected institutions. Nevertheless, students and academic staff can be regarded as potential early adopters of educational innovations, who, according to Rogers (2003, p. 249), play a crucial role in reducing uncertainty and shaping broader acceptance within social systems. Accordingly, the focus of this study is not restricted

to those with prior experience, but rather on the intention to adopt such technologies, which allows meaningful insights into perceptions and acceptance even among participants without direct exposure.

In summary, the descriptive analysis shows that the survey population is composed primarily of students, mainly from the fields of business, economics, and social sciences, and characterized by a young age structure. Moreover, direct experience with social robots is relatively rare among respondents, which has implications for the interpretation of adoption-related attitudes.

3.4.2 Test of normality

Before conducting hypothesis testing, the distribution of the central dependent construct *Intention to Adopt (MeanInt)* was examined to verify whether the assumptions of normality were met. Normality was assessed using the Kolmogorov–Smirnov and Shapiro–Wilk tests, complemented by visual inspection through histograms, Q-Q plots, and boxplots (Field, 2018, p. 393).

The results indicate a significant deviation from normality (Kolmogorov–Smirnov: D (154) = .301, p < .001; Shapiro–Wilk: W(154) = .845, p < .001). Table 3 provides the test results.

Table 3 Test of Normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
MeanInt	.301	154	<.001	.845	154	<.001

a. Lilliefors Significance Correction

Source: Own survey data, analysis with IBM SPSS Statistics

Both tests reject the null hypothesis of normal distribution. This finding is further supported by the graphical outputs. The histogram (see Figure 2) shows a bimodal distribution with peaks around values 2 (disagree) and 5 (strongly agree), while the mid-point (neutral) received fewer responses.

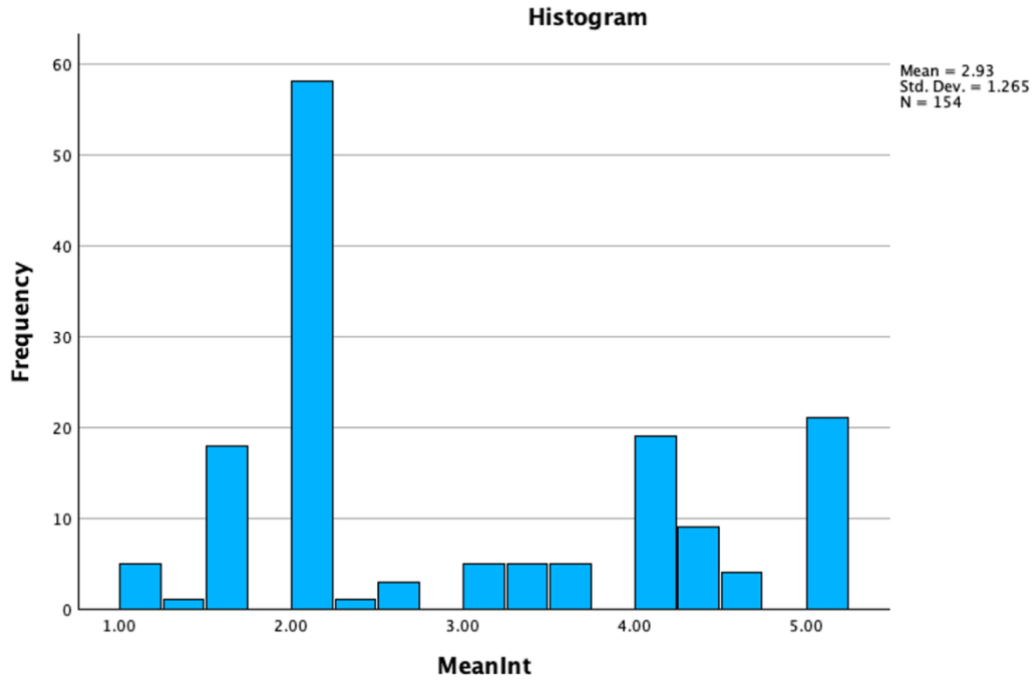


Figure 2 Histogram of the composite variable MeanInt

Source: Own survey data, analysis with IBM SPSS Statistics

Similarly, the Q-Q (Figure 3) plot displays systematic deviations from the diagonal line, and the boxplot illustrates skewness toward lower values.

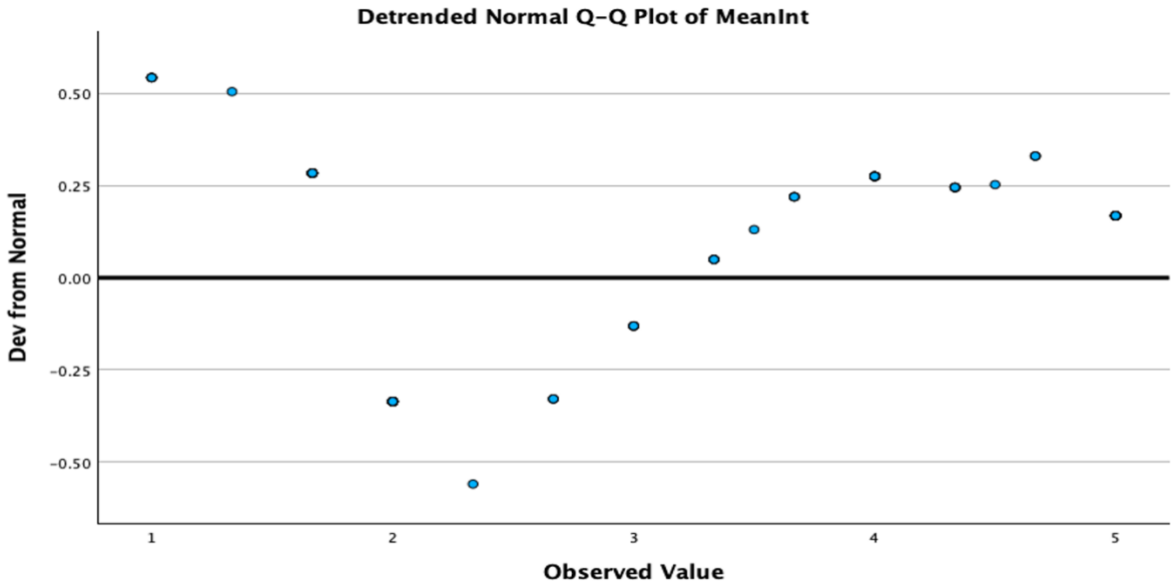


Figure 3 Q-Q Plot of the composite variable MeanInt (Intention to Adopt)

Source: Own survey data, analysis with IBM SPSS Statistics

Given these results, the assumption of normality cannot be upheld. Therefore, non-parametric methods (e.g., Spearman's rank correlation instead of Pearson's correlation) are applied in subsequent analyses to ensure robustness of statistical inference (Field, 2018, p. 439).

3.4.3 Reliability checks

Reliability analysis is commonly applied in survey research to assess the internal consistency of multi-item constructs, often using Cronbach's Alpha as an indicator (Field, 2018, p. 1190). In the present study, however, each framing dimension as well as each innovation attribute was measured with a single item. Therefore, statistical reliability checks such as Cronbach's Alpha were not applicable.

For the construct Intention to Adopt, three items were included that capture different facets of the construct (support, personal use, and recommendation). These items were averaged into a single index (MeanInt) to provide a comprehensive measure of adoption intention. Although internal consistency could not be statistically tested due to the limited number of items, the validity of the measures was ensured through their theoretical grounding in established models such as Framing Theory and the Diffusion of Innovations framework.

3.4.4 Choice of parametric vs. non-parametric tests

The distribution of the key dependent construct Intention to Adopt (MeanInt) significantly deviates from normality, as shown by the Kolmogorov-Smirnov and Shapiro-Wilk tests ($p < .001$) and confirmed through visual inspection of histograms and Q-Q plots (Section 3.4.2). For this reason, the analyses in this study are based on non-parametric statistical methods, which do not assume normal distribution of the data.

Hypothesis 1 (Framing → Intention to Adopt):

The aim of H1 is to examine whether each framing variable (Assistant, Innovation, Threat, Companion, Gimmick) is individually associated with Intention to Adopt. Since these frames represent alternative discursive narratives rather than jointly acting predictors, the analysis relies on Spearman's rank-order correlation (ρ) (Field, 2018, p. 533). This method is appropriate for detecting the strength and direction of associations without assuming linearity or normality. Pearson's product–moment correlation coefficient (r) ranges between –1 and +1, where values close to +1 indicate a strong positive relationship, values close to –1 indicate a strong negative relationship, and values around 0 suggest no linear relationship (Zar, 2005, p. 2).

Hypothesis 2 (Innovation Attributes → Intention to Adopt):

In contrast, H2 assumes that multiple innovation attributes (Relative Advantage, Compatibility, Ease of Use, Trialability, Observability, Image, Voluntariness, Visibility) may simultaneously influence adoption. Accordingly, the analysis proceeds in two steps: (1) Spearman's correlations provide an initial overview of bivariate associations (Field, 2018, p. 439), and (2) a multiple regression model is applied to examine the combined predictive power of these attributes. Regression is particularly suitable here, as innovation attributes are theoretically interrelated and may confound each other's effects. The multivariate approach makes it possible to disentangle their unique contributions and to identify the strongest drivers of adoption, consistent with Rogers' (2003) Diffusion of Innovations.

Correlation coefficients (r) can range from –1 to +1, where values closer to ±1 indicate stronger relationships. Following Asuero, Sayago and Gonzalez , coefficients above .70 are generally considered high to very high, those between .50 and .69 moderate, between .30 and .49 low, and values below .30 little if any correlation (Asuero, Sayago & Gonzalez, 2006, p. 47).

Hypothesis 3 (Experience with Social Robots → Intention to Adopt):

To compare participants with and without prior interaction experience, the Mann-Whitney U test is employed as the non-parametric equivalent of the independent samples t-test. The test statistic U can be converted into a standardized normal score (Z) for larger samples, and results are interpreted based on mean rank values (M) of the groups (Nachar, 2008, pp. 15–16).

In sum, the analysis strategy relies on Spearman's rho (ρ) for bivariate associations, the Mann-Whitney U test for group comparisons, and multiple regression models for testing combined predictor effects. This approach ensures robust and reliable results under the condition of non-normally distributed data.

4 Empirical Results

4.1 Basis of the Results and Analytical Approach

The following results are based on the cleaned dataset of N = 157 valid cases. As outlined in Chapter 3, the dependent construct Intention to Adopt (MeanInt) deviates from normality, which required the use of non-parametric procedures complemented by regression analysis.

The presentation of results proceeds in five analytical steps:

1. Analyse perceptions of social robots among students and teachers with descriptive statistics (Section 4.2; answering the first part of the RQ).
2. Test H1 by examining the relationship between framing items and Intention to Adopt (Section 4.3.1).
3. Test H2 by analysing associations between innovation attributes and Intention to Adopt (Section 4.4.1) and conduct an additional correlation analysis between framing variables and innovation attributes (Section 4.5)
4. Test H3 by comparing groups with and without prior robot interaction (Section 4.6.1)

4.2 Perceptions of Social Robots Among Students and Teachers

The descriptive results show how students and academic staff perceive social robots in higher education. The findings reveal clear patterns across framing effects and innovation attributes, which form the empirical basis for Hypotheses 1 and 2. These results complement the demographic overview presented in Chapter 3.4.1 and provide the first empirical answer to the research question by highlighting dominant and contested perceptions of social robots.

Framing effects

The results reveal substantial variation across different frames. The **Innovation frame** was perceived particularly positively: 58.2% of respondents agreed, and 15.7% strongly agreed that using social robots demonstrates that a university is innovative, while only 22.9% disagreed or strongly disagreed. A one-sample Wilcoxon signed-rank test (test value = 3) confirmed that the Innovation frame scores were significantly above the neutral midpoint ($p < .001$), indicating that respondents consistently frame social robots as signals of institutional innovativeness.

The **Companion frame** received moderate support: 36.8% agreed and 7.2% strongly agreed that interacting with a social robot could make learning more engaging, while 44.7% disagreed. The Wilcoxon test showed no significant deviation from neutrality ($p = .087$), suggesting that perceptions of robots as companions remain ambivalent and contested.

The **Assistant frame** produced similarly mixed responses. While 26.7% agreed and 13.3% strongly agreed that social robots could serve as helpful teaching assistants, a larger share of

36.7% disagreed and 16.7% strongly disagreed. The Wilcoxon test confirmed that this frame did not significantly differ from neutrality ($p = .244$). Thus, the assistant role of robots in higher education is neither strongly endorsed nor rejected by respondents.

Negative frames yielded divergent patterns. The **Threat frame**, which expressed concern about robots replacing educators, was largely rejected: 59.9% disagreed, and 14.6% strongly disagreed, whereas only 21.7% agreed or strongly agreed. Wilcoxon results showed scores significantly below the neutral midpoint ($p < .001$), indicating that replacement fears are not a dominant interpretive pattern. In contrast, the **Gimmick frame** was strongly endorsed: nearly half of respondents (49.7%) strongly agreed, and an additional 15.9% agreed that social robots represent more of a novelty or marketing tool. This was also confirmed by Wilcoxon tests, which showed scores significantly above neutrality ($p < .001$).

Taken together, these findings show clear tendencies in how respondents frame social robots. Innovation and Gimmick emerged as the dominant frames, Assistant and Companion were ambivalent, and Threat was rejected.

Perceived innovation attributes

The analysis of innovation attributes demonstrates further ambivalence. Trialability emerged as one of the most positively perceived attributes, with 63.9% agreeing and 8.9% strongly agreeing that they would have the chance to try social robots in their university. Similarly, Visibility was rated highly, with 65.1% agreement and 15.4% strong agreement, suggesting that respondents believe the use of social robots would be noticeable in academic environments. Voluntariness was also strongly supported, as 62.4% agreed and 23.6% strongly agreed that individuals should retain the freedom to decide whether to use such technology.

Other attributes, however, were viewed more critically. For Relative Advantage, almost half of the respondents (46.5% disagreed, 5.7% strongly disagreed) did not see clear benefits in using social robots, while only 34.6% expressed agreement. Compatibility was similarly rated skeptically: 40.1% disagreed and 17.2% strongly disagreed that social robots fit their learning or teaching style, whereas only 28.2% agreed. Ease of Use also showed substantial doubt, with 42.7% disagreement and only 23.7% agreement. These results suggest that while respondents value the visibility, trialability, and voluntariness of social robots, they remain unconvinced about their practical advantages and ease of integration into existing learning environments.

Overall intention to adopt

The dependent construct Intention to Adopt (see Chapter 3.2) was measured via three items: support for introduction, personal use, and recommendation. The results again show divided

opinions. For support of introduction, 21.4% agreed and 20.1% strongly agreed, but 47.1% disagreed. Similarly, for personal use, 18.5% agreed and 17.8% strongly agreed, while 51.0% disagreed. In terms of recommendation to peers, 20.7% agreed and 16.7% strongly agreed, whereas 38.9% disagreed. Taken together, the aggregated index (MeanInt) reveals that 36.9% of respondents scored at the level "2" (disagree), while only 13.6% scored the maximum value of "5" (strongly agree).

Overall, the descriptive results provide a first empirical answer to the research question: students and staff predominantly adopt Innovation and Gimmick frames, show ambivalence toward Assistant and Companion roles, and reject the Threat frame. At the same time, the findings on innovation attributes and adoption intentions highlight mixed perceptions and substantial variation in willingness to support, use, or recommend social robots. However, descriptive statistics alone cannot clarify whether and how these frames and attributes shape adoption behavior. This question is addressed in the following hypothesis tests.

4.3 Framing Patterns Related to Social Robot Integration

4.3.1 Hypothesis 1: Framing and Intention to Adopt

Although the descriptive and significance tests in Section 4.2 already provided insights into which frames are more salient among respondents: Innovation and Gimmick being dominant, Assistant and Companion perceived ambivalently, and Threat largely rejected, it remains essential to systematically test all five frames against adoption intention. The reason is twofold. First, the research design is explicitly hypothesis-driven (see Section 2.4), where each frame, both positive and negative, was operationalised as a separate construct. Second, including the full set of frames in the correlation and regression analyses provides comparability with prior international studies, where similar operationalisations were applied.

Accordingly, General Hypothesis 1 (H1) states that framing significantly influences the intention to adopt social robots in higher education, with positive frames increasing and negative frames decreasing adoption intention. More specifically, the following sub-hypotheses were tested: (H1a) the Assistant frame is positively associated with the intention to adopt, (H1b) the Innovation frame is positively associated, (H1c) the Companion frame is positively associated, (H1d) the Gimmick frame is negatively associated, and (H1e) the Threat frame is negatively associated.

To examine these hypotheses, Spearman's rank-order correlations were conducted between the framing variables and the composite measure of adoption intention (MeanInt).

Table 4 Spearman's rank-order correlations between framing variables and intention to adopt social robots

Correlations

			MeanInt	Framing_Assistant	Framing_Innovation	Framing_Threat	Framing_Companion	Framing_Gimmick
Spearman's rho	MeanInt	Correlation Coefficient	1.000	.831**	.611**	.099	.372**	-.571**
		Sig. (2-tailed)	.	<.001	<.001	.225	<.001	<.001
		N	154	149	152	151	151	149
	Framing_Assistant	Correlation Coefficient	.831**	1.000	.676**	.178*	.424**	-.593**
		Sig. (2-tailed)	<.001	.	<.001	.030	<.001	<.001
		N	149	150	149	149	149	148
	Framing_Innovation	Correlation Coefficient	.611**	.676**	1.000	-.014	.200*	-.259**
		Sig. (2-tailed)	<.001	<.001	.	.862	.014	.001
		N	152	149	153	152	151	149
	Framing_Threat	Correlation Coefficient	.099	.178*	-.014	1.000	.071	-.006
		Sig. (2-tailed)	.225	.030	.862	.	.389	.940
		N	151	149	152	152	151	149
	Framing_Companion	Correlation Coefficient	.372**	.424**	.200*	.071	1.000	-.326**
		Sig. (2-tailed)	<.001	<.001	.014	.389	.	<.001
		N	151	149	151	151	152	149
	Framing_Gimmick	Correlation Coefficient	-.571**	-.593**	-.259**	-.006	-.326**	1.000
		Sig. (2-tailed)	<.001	<.001	.001	.940	<.001	.
		N	149	148	149	149	149	150

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Source: Own survey data, analysis with IBM SPSS Statistics

The results demonstrate strong and statistically significant positive correlations for the Assistant frame (H1a; $\rho = .831$, $p < .001$) and the Innovation frame (H1b; $\rho = .611$, $p < .001$). This indicates that perceiving social robots as helpful teaching assistants or as innovative tools is strongly related to higher levels of adoption intention. A moderate positive correlation was also observed for the Companion frame (H1c; $\rho = .372$, $p < .001$), suggesting that the idea of robots as engaging companions contributes to adoption, though to a lesser extent.

In contrast, the Gimmick frame (H1d) shows a strong and significant negative correlation with adoption intention ($\rho = -.571$, $p < .001$), highlighting that when robots are perceived as mere novelties or marketing tools, acceptance is substantially reduced. The Threat frame (H1e), however, did not yield a statistically significant relationship with adoption intention ($\rho = .099$, $p = .225$), indicating that concerns about robots replacing educators do not significantly influence participants' willingness to adopt the technology.

Hypothesis 1 (H1): Framing significantly influences the intention to adopt social robots in higher education, with positive frames increasing and negative frames decreasing adoption intention. - Partially Supported.

Overall, Hypothesis 1 is partially supported. Positive frames (Assistant, Innovation, Companion) are positively related to adoption intention, and the Gimmick frame is negatively related, while the Threat frame shows no significant effect. These findings underscore the importance of how social robots are framed within higher education contexts, as the framing has a clear impact on acceptance levels.

While the framing patterns provide important insights into how social robots are perceived and how these perceptions shape adoption intentions, framing alone cannot fully account for adoption behavior. Beyond discursive representations, the decision to adopt is also influenced by concrete evaluations of the technology's characteristics. Therefore, the next section (4.4) turns to the analysis of perceived innovation attributes as predictors of adoption.

4.4 Innovation Attributes and Their Influence on Acceptance

4.4.1 Hypothesis 2: Innovation and Intention to Adopt

To test H2, Spearman's rank-order correlations were first calculated between each innovation attribute and the composite index of adoption intention (MeanInt). The sub-hypotheses specify the expected positive relationships between adoption intention and the following attributes: Relative Advantage (H2a), Compatibility (H2b), Ease of Use (H2c), Trialability (H2d), Observability (H2e), Image (H2f), Voluntariness (H2g), and Visibility (H2h) (see Appendix D, Table 11 for an overview of all hypotheses and theoretical foundations).

Table 5 Correlation matrix of innovation attributes and intention to adopt

Correlations

			MeanInt	IA_RelativeAdvantage	IA_Compatibility	IA_EaseOfUse	IA_Trialability	IA_Observability	IA_Visibility	IA_Image	IA_Voluntariness
Spearman's rho	MeanInt	Correlation Coefficient	1.000	.846**	.854**	.459**	.139	.561**	.373**	.205*	.227**
		Sig. (2-tailed)	.	<.001	<.001	<.001	.096	<.001	<.001	.012	.005
		N	154	150	146	144	144	148	149	149	152
	IA_RelativeAdvantage	Correlation Coefficient	.846**	1.000	.825**	.596**	.165	.695**	.332**	.296**	.185*
		Sig. (2-tailed)	<.001	.	<.001	<.001	.051	<.001	<.001	<.001	.025
		N	150	150	144	142	141	146	147	146	148
	IA_Compatibility	Correlation Coefficient	.854**	.825**	1.000	.450**	.189*	.654**	.344**	.343**	.190*
		Sig. (2-tailed)	<.001	<.001	.	<.001	.026	<.001	<.001	<.001	.022
		N	146	144	146	141	139	144	145	144	146
	IA_EaseOfUse	Correlation Coefficient	.459**	.596**	.450**	1.000	.302**	.508**	.311**	.297**	.185*
		Sig. (2-tailed)	<.001	<.001	<.001	.	<.001	<.001	<.001	<.001	.027
		N	144	142	141	144	138	143	143	140	143
	IA_Trialability	Correlation Coefficient	.139	.165	.189*	.302**	1.000	.167*	.409**	.381**	.022
		Sig. (2-tailed)	.096	.051	.026	<.001	.	.048	<.001	<.001	.798
		N	144	141	139	138	144	141	140	143	143
	IA_Observability	Correlation Coefficient	.561**	.695**	.654**	.508**	.167*	1.000	.201*	.233**	.053
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	.048	.	.015	.005	.526
		N	148	146	144	143	141	148	147	145	147
	IA_Visibility	Correlation Coefficient	.373**	.332**	.344**	.311**	.409**	.201*	1.000	.500**	.216**
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	.015	.	<.001	.008
		N	149	147	145	143	140	147	149	145	148
	IA_Image	Correlation Coefficient	.205*	.296**	.343**	.297**	.381**	.233**	.500**	1.000	-.011
		Sig. (2-tailed)	.012	<.001	<.001	<.001	<.001	.005	<.001	.	.890
		N	149	146	144	140	143	145	145	149	149
	IA_Voluntariness	Correlation Coefficient	.227**	.185*	.190*	.185*	.022	.053	.216**	-.011	1.000
		Sig. (2-tailed)	.005	.025	.022	.027	.798	.526	.008	.890	.
		N	152	148	146	143	143	147	148	149	152

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Source: Own survey data, analysis with IBM SPSS Statistics

The correlation analysis revealed that several innovation attributes showed strong and significant positive associations with adoption intention. In particular, Relative Advantage (H2a; $\rho = .846$, $p < .001$) and Compatibility (H2b; $\rho = .854$, $p < .001$) demonstrated the strongest correlations, confirming that respondents are more willing to adopt social robots when these are perceived as beneficial and aligned with their personal teaching or learning styles. In addition, Ease of Use (H2c; $\rho = .459$, $p < .001$), Observability (H2e; $\rho = .561$, $p < .001$), and Visibility (H2h; $\rho = .373$, $p < .001$) also showed significant positive associations, although with weaker effect sizes. Interestingly, Image (H2f; $\rho = .205$, $p = .012$) and Voluntariness (H2g; $\rho = .227$, $p = .005$) were only weakly correlated with adoption intention, while Trialability (H2d)did not reach significance ($\rho = .139$, $p = .096$).

To further assess the combined predictive power of the innovation attributes, a multiple regression analysis was conducted with adoption intention (MeanInt) as the dependent variable.

Table 6 Regression model summary and coefficients table

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.917[a]	.841	.831	.52713	.841	82.655	8	125	<.001

a. Predictors: (Constant), IA_Voluntariness, IA_Observability, IA_Trialability, IA_Image, IA_EaseOfUse, IA_Visibility, IA_Compatibility, IA_RelativeAdvantage

Source: Own survey data, analysis with IBM SPSS Statistics

The regression model was highly significant ($F(8,125) = 82.655$, $p < .001$) and explained 84.1% of the variance in adoption intention ($R^2 = .841$). Among the predictors, Relative Advantage (H2a; $\beta = .599$, $p < .001$) and Compatibility (H2b; $\beta = .460$, $p < .001$) emerged as the strongest positive predictors, followed by Visibility (H2h; $\beta = .216$, $p < .001$). These results confirm that perceiving social robots as beneficial, compatible, and visible within the educational environment substantially increases the likelihood of adoption.

However, two predictors showed significant negative effects: Observability (H2e; $\beta = -.195$, $p = .001$) and Image (H2f; $\beta = -.216$, $p < .001$). This suggests that when the outcomes of social robot use are perceived as overly observable, or when adoption is primarily associated with status-related motives (i.e., improving one's image), the willingness to adopt decreases. By contrast, Ease of Use (H2c), Trialability (H2d), and Voluntariness (H2g) did not yield statistically significant effects in the regression model, indicating that these factors do not play a decisive role in shaping adoption intention in the given context.

Hypothesis 2 (H2): Positive perceptions of innovation attributes are positively associated with the intention to adopt social robots in higher education. - Partially Supported.

Taken together, these findings provide strong support for H2a, H2b, and H2h, partial support for H2c, H2e, H2f, and H2g, while H2d is not supported. Hence, Hypothesis 2 is only partially supported. Innovation attributes overall are strong predictors of adoption intention, but the effects are heterogeneous: while Relative Advantage, Compatibility, and Visibility significantly enhance acceptance, the roles of Observability and Image are unexpectedly negative, and other attributes (Ease of Use, Trialability, Voluntariness) appear less influential. This underlines the complexity of innovation perceptions in higher education and suggests that students and staff base their adoption intentions primarily on the practical benefits and contextual fit of social robots, rather than on usability or voluntariness.

4.5 Correlation between Innovation Attributes and Framing

While Hypothesis 1 (Section 4.3) demonstrated that framing patterns significantly influence adoption intention, and Hypothesis 2 (Section 4.4) established that innovation attributes serve as strong predictors of adoption, the relationship between these two explanatory dimensions has not yet been explored. To provide a more comprehensive picture of how perceptions of social robots are formed, additional analyses were conducted to examine correlations between framing variables and innovation attributes. This step allows us to assess whether specific frames align with particular evaluations of technological characteristics (see Appendix F, Table 16).

The results reveal clear systematic patterns. Positive frames are strongly associated with favorable evaluations of innovation attributes. For example, Framing_Assistant shows strong positive correlations with Relative Advantage ($\rho = .814$, $p < .001$) and Compatibility ($\rho = .816$, $p < .001$), indicating that respondents who perceive robots as helpful assistants are also more likely to view them as beneficial and aligned with their own study or teaching practices. Similarly, Framing_Innovation is positively correlated with Compatibility ($\rho = .668$, $p < .001$), Observability ($\rho = .355$, $p < .001$), and Visibility ($\rho = .480$, $p < .001$), reflecting that the "innovation" narrative resonates most when social robots are seen as demonstrably useful and visible in practice. The Companion frame also yields notable positive associations, particularly with Ease of Use ($\rho = .633$, $p < .001$) and Relative Advantage ($\rho = .570$, $p < .001$), suggesting that robots framed as companions are more easily linked to usability and experiential benefits.

In contrast, the Gimmick frame is consistently negatively associated with innovation attributes. Strong negative correlations are observed with Relative Advantage ($\rho = -.581$, $p < .001$), Compatibility ($\rho = -.513$, $p < .001$), and Observability ($\rho = -.518$, $p < .001$). This

highlights that when robots are perceived as novelties or superficial marketing tools, they are simultaneously judged as lacking concrete benefits, fit, or visible educational outcomes. Interestingly, the Threat frame again does not produce strong or consistent correlations, underscoring the earlier finding (Section 4.3.1) that concerns about replacement are not a central dimension shaping respondents' technological evaluations.

Taken together, these results show that framing and innovation attributes are not independent but strongly intertwined. Positive frames (Assistant, Innovation, Companion) reinforce favorable assessments of utility, compatibility, and usability, while negative frames, particularly Gimmick, undermine such evaluations. This finding provides an important bridge between the analyses in Sections 4.3 and 4.4: while framing operates at the discursive level and innovation attributes at the evaluative level, both dimensions appear to mutually reinforce each other in shaping adoption intentions.

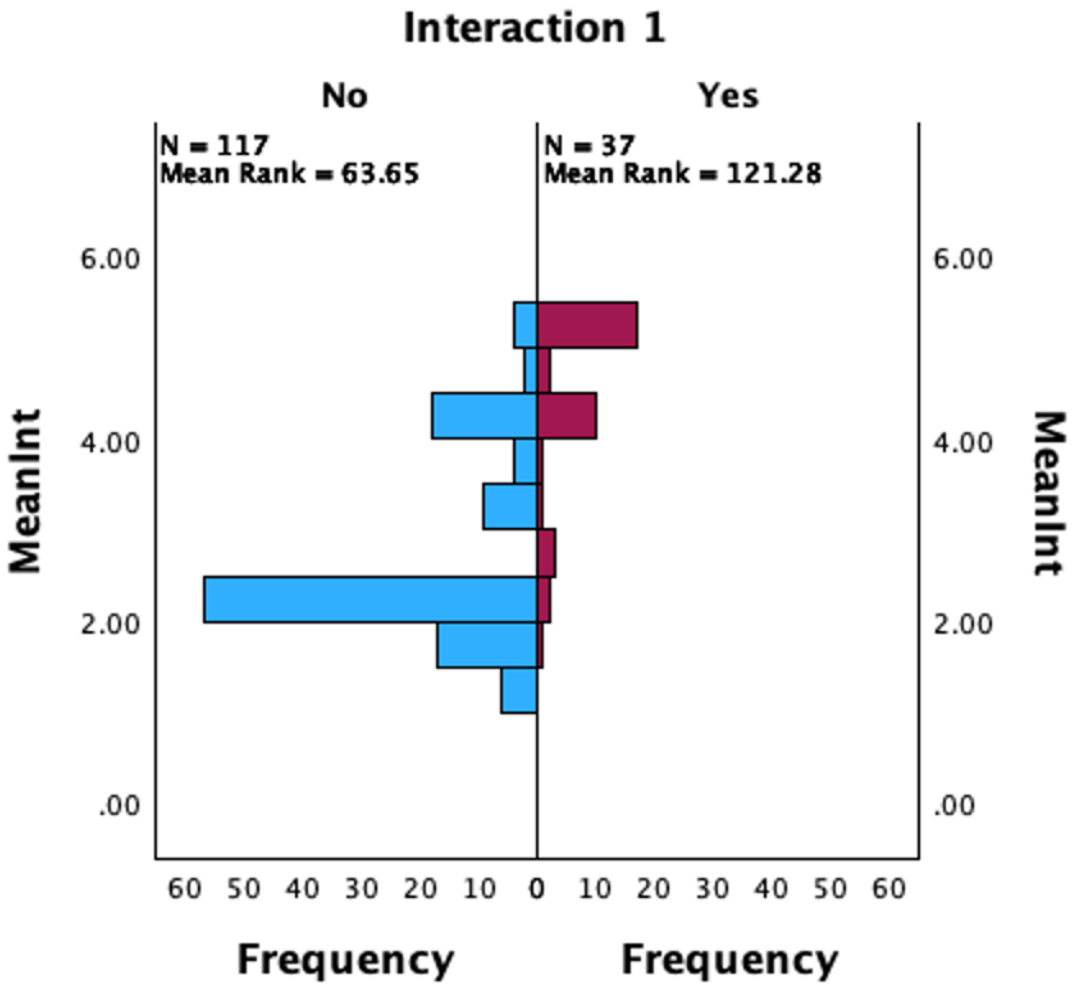
In the next section (4.6), the analysis turns to the role of direct experience with social robots, which provides an additional layer of explanation for variations in adoption intention across respondents.

4.6 Experience with Social Robots and Intention to Adopt

4.6.1 Hypothesis 3: Experience and Intention to Adopt

Hypothesis 3 predicted that respondents with prior interaction experience with social robots would report a higher intention to adopt than those without such experience (*see Section 2.4*). To test this assumption, an Independent-Samples Mann-Whitney U test was conducted, given that the dependent variable *Intention to Adopt* did not meet the assumptions of normality (*see Section 3.4.2*).

Table 7 Independent-Samples Mann-Whitney U Test



Source: Own survey data, analysis with IBM SPSS Statistics

The results show a significant difference in adoption intention between the two groups ($U = 544.50$, $Z = -7.07$, $p < .001$). Respondents with prior interaction experience ($n = 37$) had a substantially higher mean rank ($M = 121.28$) compared to those without such experience ($n = 117$, $M = 63.65$). This indicates that previous exposure to social robots is strongly associated with greater willingness to adopt them in higher education.

From a theoretical perspective, these findings can be explained through the lens of Rogers' *Diffusion of Innovations* (*see Section 2.3*). The attribute of *trialability* suggests that the opportunity to test or directly engage with an innovation reduces uncertainty and fosters adoption (Rogers, 2003, p. 16). In this study, prior interaction with robots at the university functions as a tangible form of trialability: respondents who had already experienced the

technology were more confident and open toward its adoption, while those without such experience tended to remain more skeptical.

Hypothesis 3 (H3): Individuals with prior experience with social robots demonstrate a higher intention to adopt than those without prior experience. - Supported.

Taken together, these findings provide clear support for Hypothesis 3. Experience with social robots appears to be a decisive factor in shaping acceptance, confirming the relevance of experiential familiarity for technology adoption. This outcome also complements the results of Hypotheses 1 and 2: while framing (Section 4.3) and perceived innovation attributes (Section 4.4) play an important role in influencing acceptance, direct interaction offers a concrete experiential basis for forming adoption intentions. In this sense, prior exposure to social robots reduces uncertainty and increases confidence in their potential benefits, thereby strengthening adoption readiness.

5 Discussion

5.1 Critical Reflection on Research Design and Limitations

The chosen quantitative survey design proved appropriate for addressing the research question and testing the hypotheses. By operationalizing framing effects, innovation attributes, and adoption intentions into measurable constructs, the study generated systematic and interpretable insights. The standardized questionnaire ensured comparability across participants, while the theoretical framework provided conceptual clarity.

At the same time, several limitations need to be acknowledged. The sample was predominantly composed of students, with staff and professors represented only marginally, and the disciplinary distribution was skewed toward business and social sciences. This restricts the generalizability of the findings. The measurement strategy relied mainly on single-item indicators, which reduced reliability compared to multi-item scales, though it kept the survey concise. From a statistical perspective, the non-normal distribution of the dependent variable necessitated the use of non-parametric tests, which offer lower statistical power compared to parametric alternatives. Moreover, the subgroup with prior robot experience was small, which limited the robustness of group comparisons. Finally, reliance on self-reported data raises the possibility of response biases, and the study captures intentions rather than actual behavior.

Despite these limitations, the methodological approach proved suitable for an exploratory, hypothesis-driven study, yielding meaningful results. Future research could address the identified weaknesses by including more diverse samples, employing multi-item scales, and using longitudinal or experimental designs to capture adoption dynamics more comprehensively.

5.2 Interpretation of Results

Answer to RQ Part 1: How do students and academic staff in German higher education frame the integration of social robots?

The descriptive and inferential analyses show that students in Germany predominantly frame social robots through two lenses: Innovation and Gimmick. The Innovation frame, endorsed by nearly three quarters of respondents (see Section 4.2), positions robots as symbols of modernisation and competitiveness, aligning with findings from international studies that highlight the association between robots and digital transformation (Aoun, 2017; Lehmann & Svarny, 2021). At the same time, however, almost two thirds of respondents endorsed the Gimmick frame, perceiving robots as superficial novelties lacking substantive educational value. This ambivalence is less pronounced in some international contexts, where positive

frames, such as "Assistant" or "Companion," are reported as more dominant (Belpaeme et al., 2018; Johal, 2020). In contrast, German respondents expressed greater skepticism, reflecting a cautious, critical orientation toward technological integration in higher education.

The Assistant and Companion frames received more divided responses: while a minority viewed robots as potentially helpful teaching aides or engaging companions, larger groups remained uncertain or skeptical. Finally, the Threat frame was largely rejected, with most respondents not believing that robots would replace human educators. This again differs from findings in East Asian contexts, where substitution fears are more salient (see van Ewijk et al., 2020).

In sum, the German case shows that social robots are simultaneously framed as innovative and as gimmicks, with ambivalence about their pedagogical usefulness and little concern about substitution. This provides a nuanced empirical answer to the first part of the RQ, highlighting that German students predominantly interpret social robots through competing frames of progressive innovation and superficial novelty, while other frames play only secondary roles.

Answer to RQ Part 2: What impact do these frames have on their acceptance of the technology? The hypothesis testing confirms that framing significantly influences adoption intention, thereby addressing the second part of the RQ. Positive frames are associated with higher willingness to adopt: the Assistant ($\rho = .831$, $p < .001$) and Innovation ($\rho = .611$, $p < .001$) frames were the strongest predictors, while the Companion frame also contributed moderately ($\rho = .372$, $p < .001$). In contrast, the Gimmick frame strongly reduced adoption intention ($\rho = -.571$, $p < .001$), confirming that when robots are perceived as superficial novelties, they are unlikely to be accepted. Interestingly, the Threat frame had no significant effect ($\rho = .099$, $p = .225$), suggesting that replacement fears do not influence German students' adoption decisions.

This finding both confirms and nuances international research. It aligns with studies showing that positive framings foster openness and trust (Belpaeme et al., 2018; Donnermann et al., 2022), but diverges from contexts where the Threat frame strongly predicts rejection (Smakman et al., 2021). Thus, in Germany, skepticism about substantive value (Gimmick) matters more for adoption than concerns about job replacement (Threat).

Overall Conclusion for the Research Question

The findings demonstrate that in German higher education, social robots are primarily framed as either innovative tools or superficial novelties, and these interpretations directly affect acceptance. Positive framings, especially Assistant and Innovation, increase willingness to

adopt, while negative framings, such as Gimmick, reduce it. The Threat frame does not play a meaningful role. Accordingly, the research question can be answered as follows: students and academic staff view social robots both as signs of innovation and as superficial novelties, and these views strongly influence their intention to adopt.

5.3 Contribution to Research and Practice

Recommendation 1: Position robots as assistants with clear pedagogical value

A key finding of this study is that framing strongly shapes adoption. The Assistant frame was the most powerful positive predictor of intention to adopt ($\rho = .831, p < .001$), followed by Innovation ($\rho = .611, p < .001$). In addition, Relative Advantage ($\beta = .599, p < .001$), Compatibility ($\beta = .460, p < .001$), and Visibility ($\beta = .216, p < .001$) emerged as critical drivers of acceptance. Prior experience with robots also proved decisive in increasing willingness to adopt ($U = 544.50, p < .001$).

Based on these results, it might be recommended that German universities consider integrating social robots into language support programmes, particularly preparatory DSH courses for international students. In this context, robots could serve as standardized speaking partners for practicing pronunciation, dialogues, and exam simulations. The structured nature of DSH examinations makes this a feasible and low-stakes entry point. Such integration would align directly with the Assistant frame, demonstrate pedagogical value, and provide students with early positive experiences that reduce novelty effects and skepticism. HRW could serve as a pilot example, but the approach is transferable to other institutions that offer DSH preparatory courses. Evidence from robot-assisted language learning further supports this recommendation, showing positive effects on oral competence (Lee & Lee, 2022).

Stepwise integration in DSH courses thus offers German universities a practical way to build familiarity and acceptance. Students who first encounter robots as supportive assistants are more likely to perceive them as useful educational tools rather than superficial novelties.

Recommendation 2: Avoid gimmick framings and excessive emphasis on visibility or image

One of the most critical findings of this study concerns the risks associated with the Gimmick frame. Section 4.3.1 (H1) revealed that perceiving robots as novelties strongly reduces adoption intention ($\rho = -.571$, $p < .001$). Similarly, regression results in Section 4.4.1 (H2) showed that Image ($\beta = -.216$, $p < .001$) and Observability ($\beta = -.195$, $p = .001$) can negatively affect adoption when overemphasised, suggesting that prestige-driven or PR-oriented positioning fosters skepticism rather than trust.

A real-world example of this effect occurred in 2024 at D'Youville University (Buffalo, USA), where the humanoid robot Sophia (Hanson Robotics) delivered a commencement address. While the event drew media attention, it was criticised by students and faculty as a superficial publicity stunt. A petition was even launched demanding that human speakers be prioritised for such milestones (The Sun, 2024). This case illustrates the reputational risks of positioning robots as symbolic novelties rather than pedagogical tools.

For the German context, this finding is particularly relevant. As demonstrated in Section 5.2, German respondents strongly endorsed the Gimmick frame, far more than the Threat frame. This indicates that skepticism about substantive value is the primary barrier in Germany. German universities therefore need to be especially cautious not to use robots as "eye-catchers" at events or as branding instruments.

Instead, communication strategies should highlight tangible contributions to learning and institutional processes. Robots should be embedded in authentic tasks, for example exam simulations, oral practice, or structured exercises, rather than symbolic roles. By reducing reliance on image and prestige, institutions can strengthen trust in robots as legitimate tools, mitigating the risk of user disappointment and rejection.

6 Conclusion

6.1 Summary of Key Findings

This thesis set out to examine how social robots are framed in higher education and how these framings, alongside perceptions of innovation attributes and prior experience, shape the intention to adopt. Three main findings emerged.

First, framing effects (H1) proved decisive.

The analysis demonstrated that positive frames, particularly Assistant ($\rho = .831$, $p < .001$) and Innovation ($\rho = .611$, $p < .001$), are strongly associated with higher adoption intentions, whereas the Gimmick frame exerts a substantial negative influence ($\rho = -.571$, $p < .001$). By contrast, the Threat frame had no significant effect ($\rho = .099$, $p = .225$). An important nuance is that the Assistant frame was not among the most widely endorsed framings in descriptive terms (see Section 4.2), yet for those respondents who did identify with it, it became the strongest predictor of adoption. This highlights that prevalence and predictive power must be distinguished: even less frequent framings can exert a disproportionately strong influence on acceptance. Overall, these findings confirm that communicative positioning is not a peripheral factor but a central determinant of adoption willingness: when robots are presented as pedagogically useful assistants, acceptance rises, while gimmick-oriented portrayals generate skepticism.

Second, innovation attributes (H2) emerged as crucial predictors.

In line with Rogers' Diffusion of Innovations theory, Relative Advantage ($\beta = .599$, $p < .001$) and Compatibility ($\beta = .460$, $p < .001$) were found to be the strongest drivers of adoption, with Visibility playing a smaller yet significant role ($\beta = .216$, $p < .001$). Interestingly, Image and Observability showed negative effects when overemphasised, suggesting that positioning robots primarily as prestige objects or focusing too heavily on their demonstrability can undermine acceptance. These findings nuance Rogers' framework by showing that in the higher education context, not all attributes contribute positively: perceptions of symbolic or superficial value may reduce willingness to adopt.

Third, prior experience (H3) proved highly influential.

Respondents with direct exposure to social robots reported significantly higher adoption intentions than those without ($M = 121.28$ vs. 63.65; $U = 544.50$, $p < .001$). This confirms the role of experiential familiarity in reducing uncertainty, building trust, and transforming abstract technology into a tangible educational resource. From a practical perspective, it underlines the necessity of structured opportunities, such as pilot projects and demonstrations, that enable early and low-stakes interaction with robots.

Taken together, these results show that successful integration of social robots requires a threefold strategy: discursive positioning that avoids gimmick framings, practical alignment through demonstrable advantages and contextual fit, and experiential exposure that normalises interaction. These three dimensions directly informed the practical recommendations presented in Section 5.3.

6.2 Final Conclusion and Answer to Research Question

The central research question of this study was:

How do students and academic staff in German higher education frame the integration of social robots, and what impact do these frames have on their acceptance of the technology?

Answer to Part 1 (Framing patterns).

In the German higher education context, social robots are primarily interpreted in two competing ways: as innovative tools that symbolise modernisation, or as gimmicks that serve little more than symbolic or publicity functions. The Innovation frame received broad support, while the Gimmick frame was also widely endorsed, reflecting a certain ambivalence about the added pedagogical value. Other framings, such as Assistant and Companion, were less widespread, and the Threat frame was largely rejected, indicating that fears of replacement play little role compared to doubts about usefulness.

Answer to Part 2 (Impact on acceptance).

Despite being less widespread, the Assistant frame exerted the strongest positive influence on adoption intentions ($\rho = .831$, $p < .001$), followed by Innovation ($\rho = .611$, $p < .001$) and, to a lesser degree, Companion ($\rho = .372$, $p < .001$). By contrast, the Gimmick frame significantly reduced willingness to adopt ($\rho = -.571$, $p < .001$), while the Threat frame had no measurable effect. This indicates that prevalence and impact diverge: although not dominant in descriptive terms, the Assistant frame has the greatest predictive power for acceptance.

6.3 Implications and Outlook

This study shows that the adoption of social robots in higher education depends strongly on how they are framed and embedded in everyday academic contexts.

Policy and Institutional Strategy.

For universities, the key is to frame robots as pedagogical assistants rather than novelties. The Assistant frame strongly increases adoption, while the Gimmick frame reduces it. Projects should therefore be clearly linked to learning outcomes, highlight added value, and manage expectations through transparent communication.

Practice.

Robots should be used in teaching contexts where their benefits are visible, such as tutoring or language support. Early pilot projects, for example in preparatory language courses, can provide students with positive first experiences. Teachers should be involved through training and co-design to ensure relevance and acceptance.

Future Research.

Further studies should test causal framing effects, track changes in acceptance over time, and examine actual learning outcomes rather than only intentions. Pilot projects in preparatory language courses such as the DSH could serve as a valuable research setting, as they provide structured, low-stakes opportunities to study how robots function as assistants in practice. Future work should also address current limitations by including a more diverse sample of disciplines and staff groups and by complementing self-reported data with behavioral or longitudinal measures.

Outlook.

The outlook is cautiously optimistic: ambivalence remains, but acceptance grows when robots are framed as assistants and provide clear educational benefits. Low-stakes pilot projects can pave the way for broader integration, helping universities move from novelty use to meaningful adoption in teaching and learning.

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Appendix

Appendix A: Questionnaire of the study with origin of the constructs

Appendix B: Distribution of the survey

Appendix C: Graphical representation of the online questionnaire Sosci Survey (from a participant's perspective)

Appendix D: Overview of Hypotheses and Theoretical Foundations

Appendix E: Survey Completion Statistics (SoSci Survey)

Appendix F: SPSS Output Tables

Appendix A: Questionnaire of the study with origin of the constructs

Table 8 Overview of Variable Coding

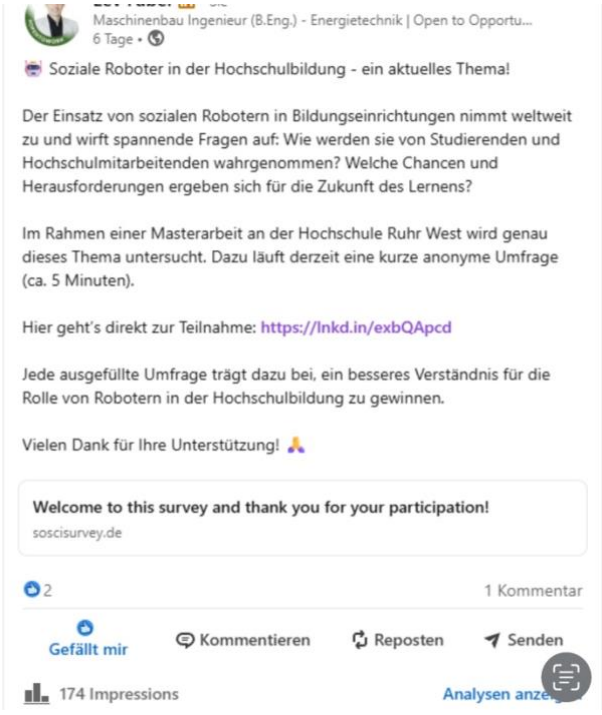
Before (Original Item / SoSci Code)	After (SPSS Variable Name)	Construct
F101_01 -"Framing: A social robot can function as a helpful teaching assistant for instructors in higher education."	Framing_Assistant	Framing (positive)
F101_02 - "Framing: Using social robots in the classroom demonstrates that a university is innovative."	Framing_Innovation	Framing (positive)
F101_03 - "Framing: I am worried that social robots could replace human educators."	Framing_Threat	Framing (negative)
F101_05 - "Framing: Interacting with a social robot can make learning more engaging by giving students a feeling of having a friendly companion in class."	Framing_Companion	Framing (positive)
F101_04 - "Framing: Social robots in higher education are more of a novelty or marketing	Framing_Gimmick	Framing (negative)

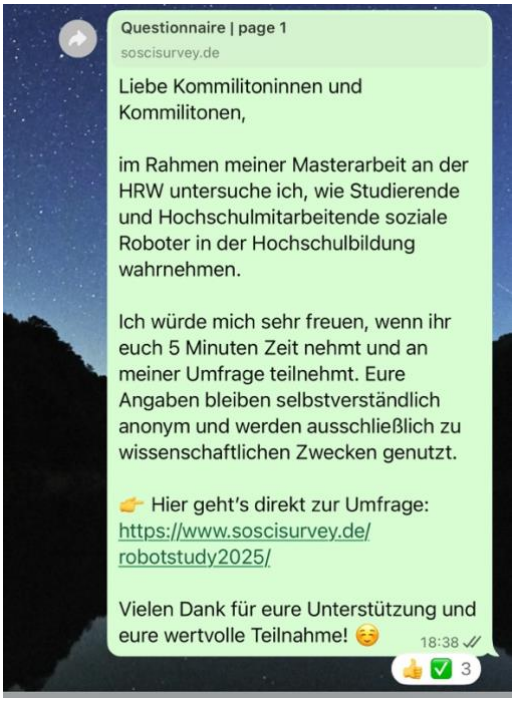
gimmick than a truly useful tool.”		
IA01_01 - “Rogers, Moore: Using a social robot would improve the quality of teaching.”	IA_RelativeAdvantage	Innovation Attribute
IA01_02 - “Rogers, Moore: A social robot fits well with my teaching/learning style.”	IA_Compatibility	Innovation Attribute
IA01_03 - “Rogers, Moore: The functions of a social robot are easy to understand and use.”	IA_EaseOfUse	Innovation Attribute
IA01_04 - “Rogers, Moore: I believe I would have the chance to try a social robot at my university.”	IA_Trialability	Innovation Attribute
IA01_05 - “Rogers, Moore: The outcomes of using a social robot in education are easy to observe and explain.”	IA_Observability	Innovation Attribute
IA01_07 - “Rogers, Moore: The presence of a social robot in education attracts attention and interest.”	IA_Visibility	Innovation Attribute
IA01_06 - “Rogers, Moore: Using a social robot would improve how others perceive me as a progressive educator/student.”	IA_Image	Innovation Attribute
IA01_08 - “Rogers, Moore: I would prefer to have the freedom to choose whether or not to use a social robot in my work/study.”	IA_Voluntariness	Innovation Attribute

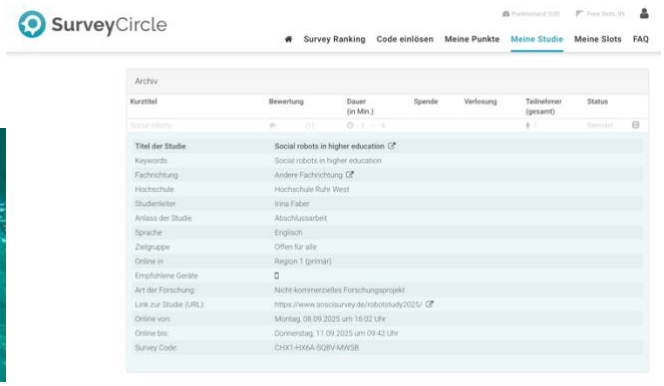
IT01_01 - “Interaction: I would support the introduction of a social robot in my university.”	Intention_Support	Intention to Adopt
IT01_02 - “Interaction: If I had access to a social robot, I would use it in my teaching/learning activities.”	Intention_Use	Intention to Adopt
IT01_03 - “Interaction: I would recommend that colleagues or fellow students try using a social robot.”	Intention_Recommend	Intention to Adopt
Computed Variable (Mean of IT01_01, IT01_02, IT01_03)	MeanInt	Intention to Adopt (composite)

Source: Own formulation (SPSS coding)

Appendix B: Distribution of the survey







Appendix C: Graphical representation of the online questionnaire Sosci Survey (from a participant's perspective)

Figure 4 Survey Introduction

Figure 5 Survey Question 2

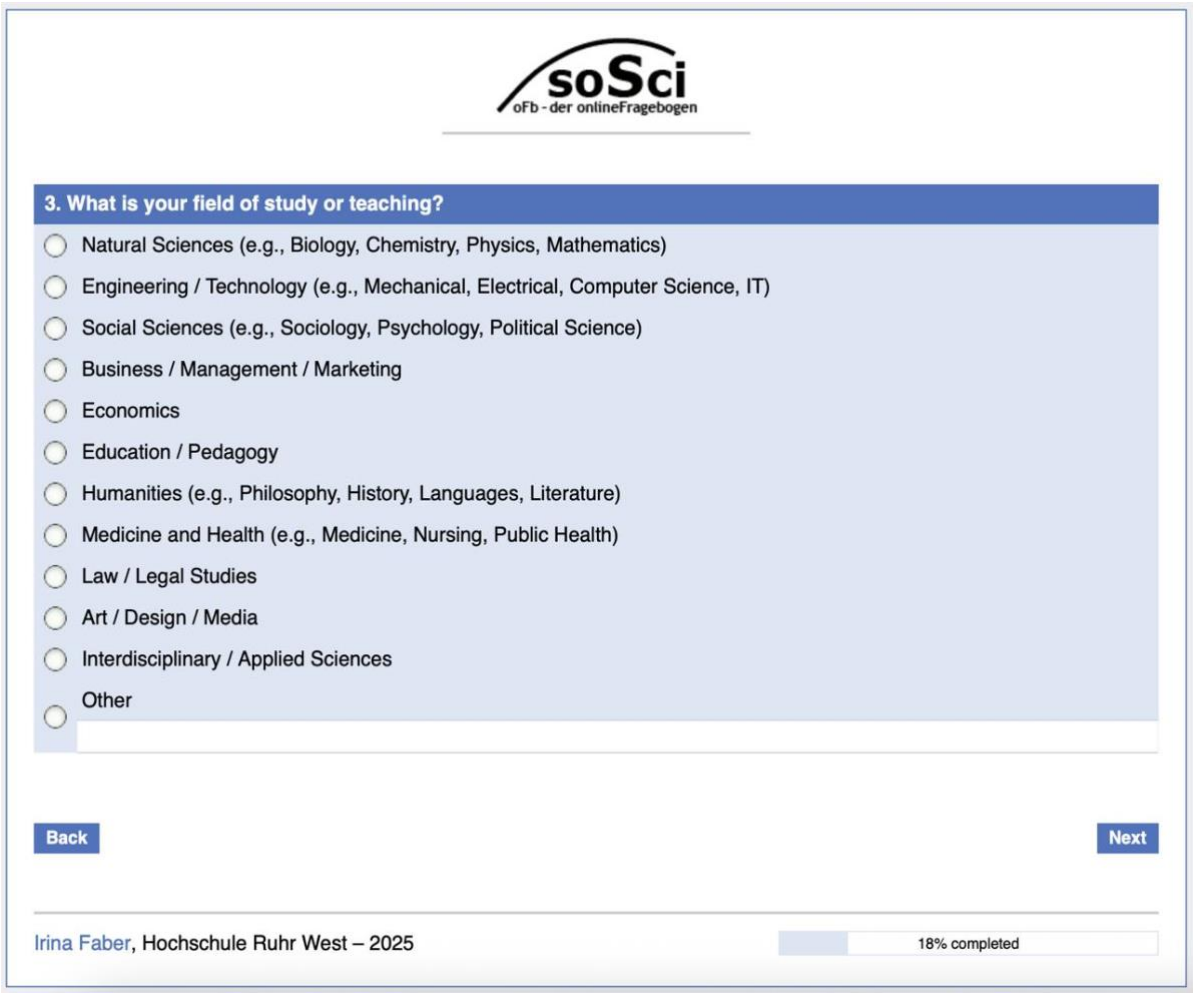


Figure 6 Survey Question 3

Figure 7 Survey Question 4

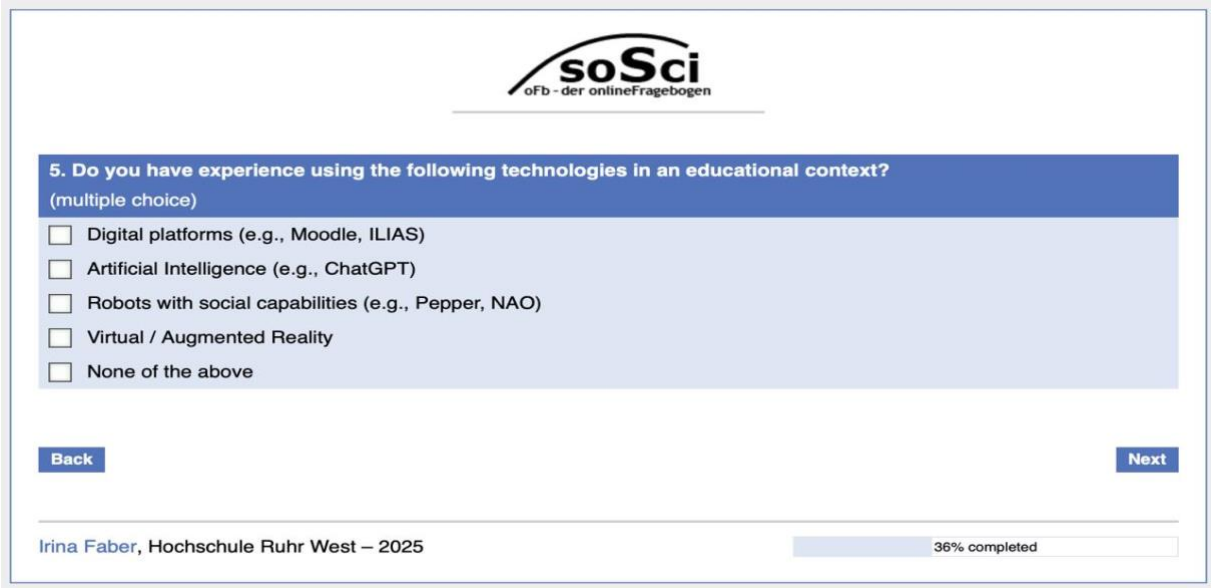


Figure 8 Survey Question 5

Figure 9 Survey Question 6

Figure 10 Survey: Social Robot Defenition

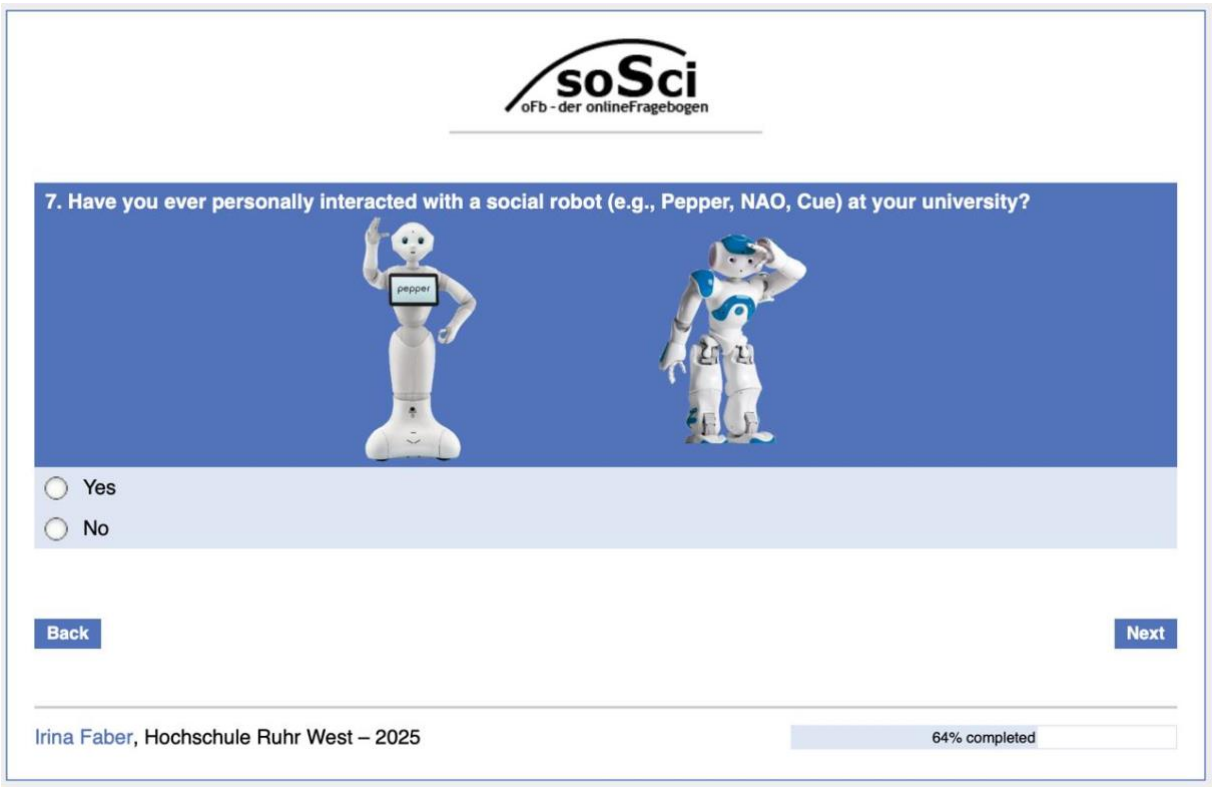


Figure 11 Survey Question 7

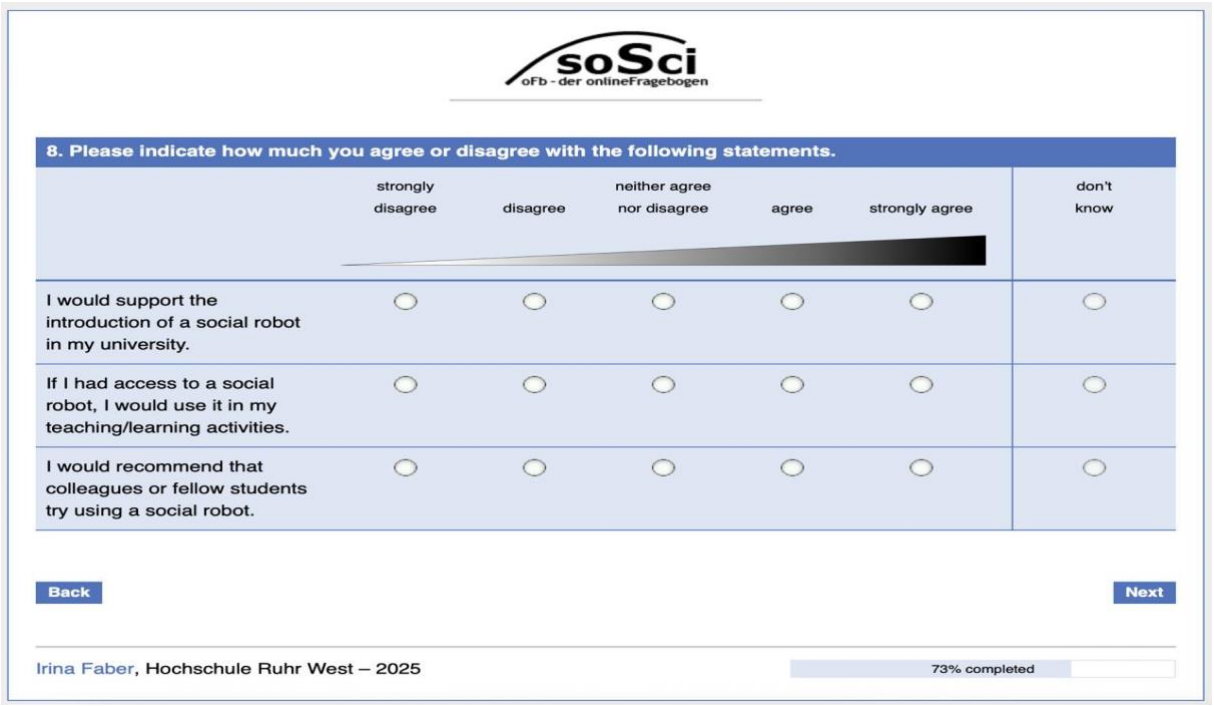


Figure 12 Survey Question 8

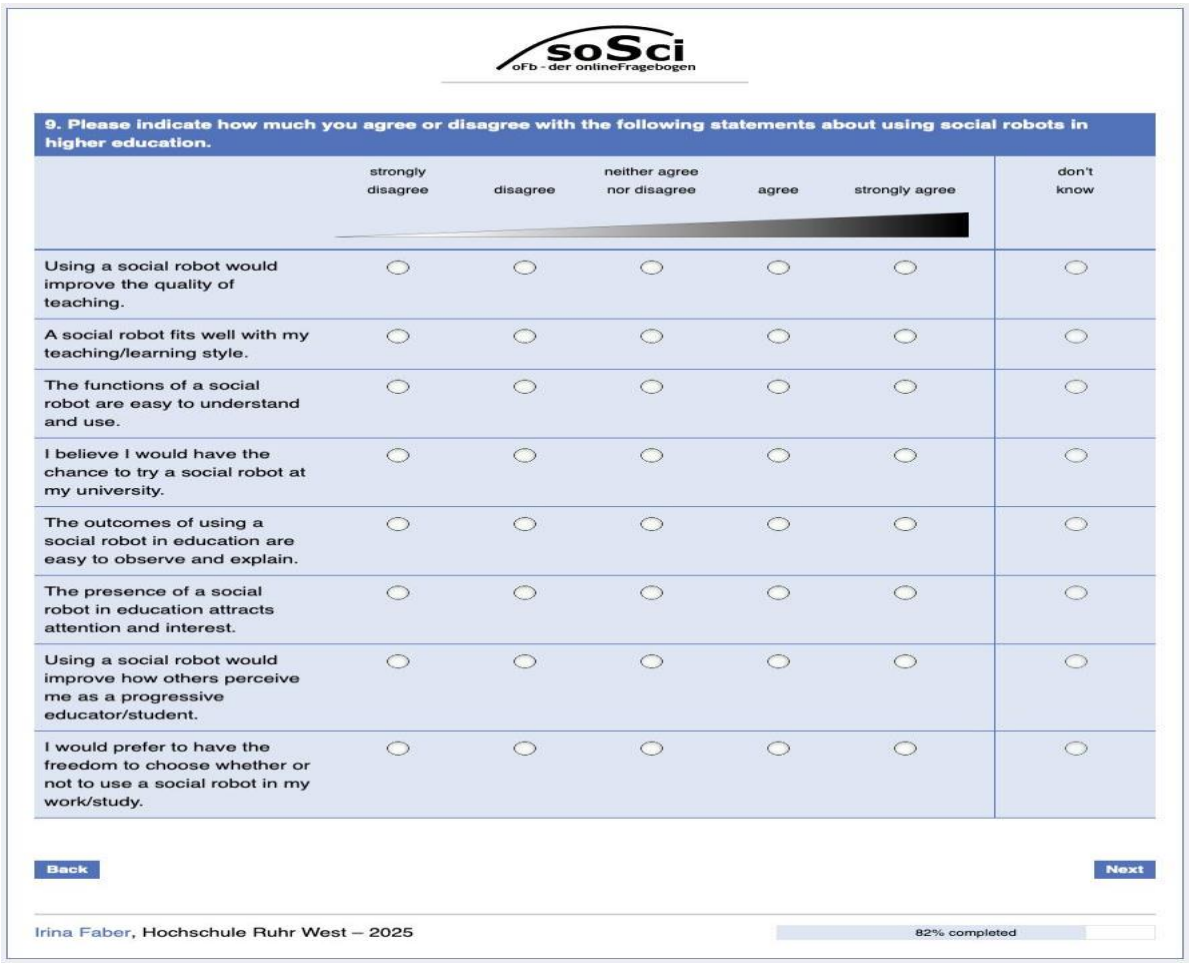
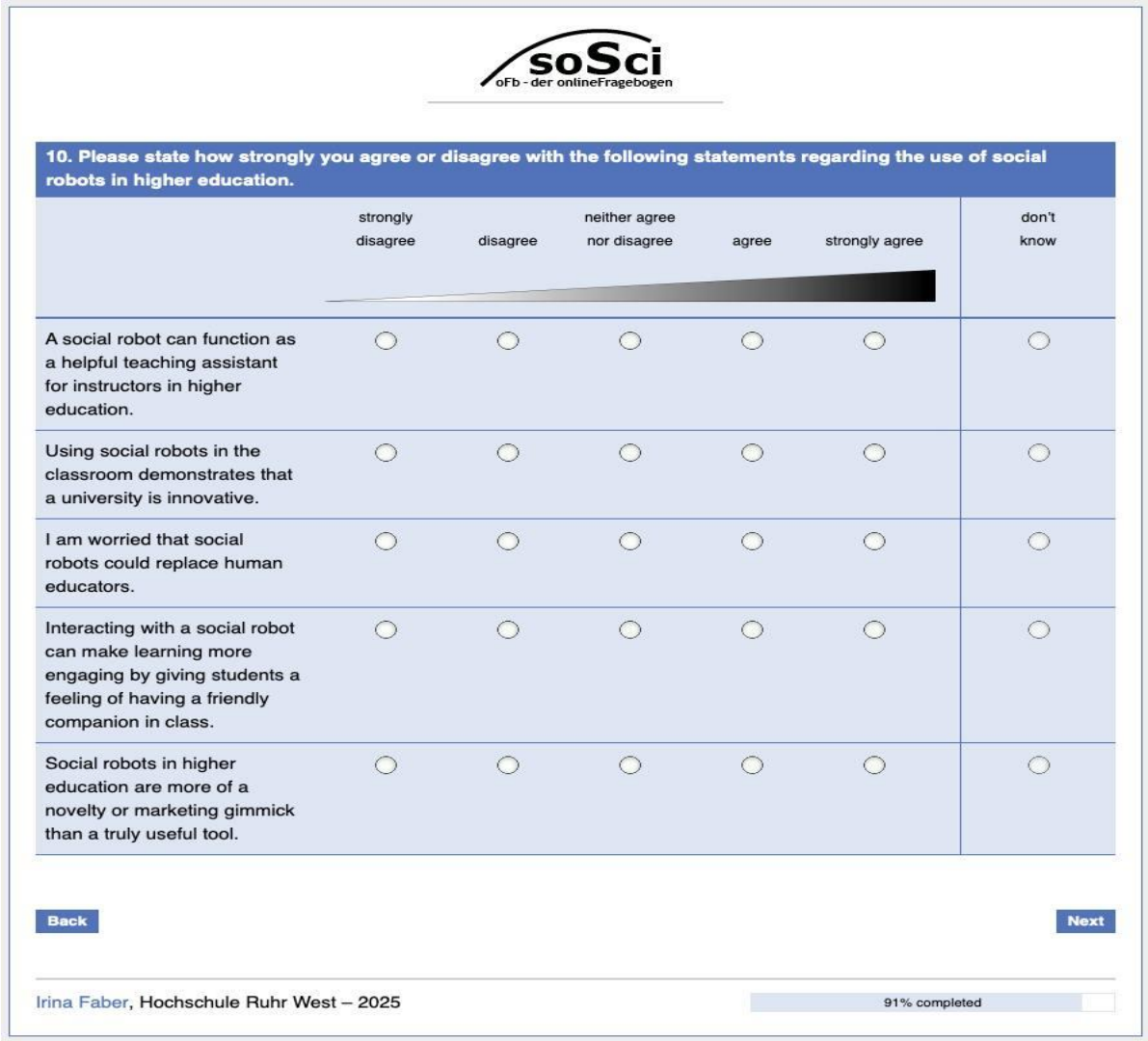


Figure 13 Survey Question 9



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oFb - der onlineFragebogen

10. Please state how strongly you agree or disagree with the following statements regarding the use of social robots in higher education.

	strongly disagree	disagree	neither agree nor disagree	agree	strongly agree	don't know
A social robot can function as a helpful teaching assistant for instructors in higher education.	○	○	○	○	○	○
Using social robots in the classroom demonstrates that a university is innovative.	○	○	○	○	○	○
I am worried that social robots could replace human educators.	○	○	○	○	○	○
Interacting with a social robot can make learning more engaging by giving students a feeling of having a friendly companion in class.	○	○	○	○	○	○
Social robots in higher education are more of a novelty or marketing gimmick than a truly useful tool.	○	○	○	○	○	○

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Irina Faber, Hochschule Ruhr West – 2025 91% completed

Figure 14 Survey Question 10

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Thank you for your participation!

Your input is highly valuable and will contribute to a better understanding of how emerging technologies like social robots are viewed and evaluated within higher education.

SurveyCircle Code: CHX1-HX6A-SQ8V-MWSB

Conducted by:
Irina Faber - irina.faber@stud.hs-ruhrwest.de

Irina Faber, Hochschule Ruhr West – 2025

Figure 15 Survey Thankful Page

Appendix D: Overview of Hypotheses and Theoretical Foundations

Table 9 Summary of Hypotheses (H1-H3), Sub-Hypotheses, and Underlying Theories

Hypothesis	Sub-Hypotheses	Theory / Source
H1: Framing and Intention to Adopt **General Hypothesis 1 (H1):** ***Framing significantly influences the intention to adopt social robots in higher education, with positive frames increasing and negative frames decreasing adoption intention.***	H1a: Assistant frame → positive adoption intention H1b: Innovation frame → positive adoption intention H1c: Companion frame → positive adoption intention H1d: Gimmick frame → negative adoption intention H1e: Threat frame → negative adoption intention	**Framing Theory** (Goffman, 1986, p. 21; Entman, 1993, p. 52; see Section 2.2.1). Application to education: Belpaeme et al., 2018, pp. 2-6; Donnermann et al., 2022, pp. 3-5; Johal, 2020, pp. 77-78; van Ewijk et al., 2020, pp. 4, 8-9; Rasmussen et al., 2024; Hu, 2021; Smakman et al., 2021, p. 13; Torras, 2023, p. 7; Aoun, 2017, pp. 13-15; Lehmann & Svarny, 2021, p. 284; Holmes, Fadel & Bialik, 2019, p. 11 (see Section 2.2.2).
H2: Innovation Attributes and Intention to Adopt **General Hypothesis 2 (H2):** ***Positive perceptions of innovation attributes are positively associated with the intention to adopt social robots in higher education.***	H2a: Relative advantage → positive adoption intention H2b: Compatibility → positive adoption intention H2c: Ease of use → positive adoption intention H2d: Trialability → positive adoption intention H2e: Observability → positive adoption intention H2f: Image → positive adoption intention H2g: Voluntariness → positive adoption intention H2h: Visibility → positive adoption intention	**Diffusion of Innovations** (Rogers, 2003, pp. 41-42, 246-247; see Section 2.3.1). **Perception Model** (Moore & Benbasat, 1991, p. 195; see Section 2.3.2). Empirical applications in higher education: Straub, 2009, p. 637; Sahin, 2006, p. 14; Rudolph et al., 2016,

		pp. 5-6 (see Section 2.3.3).
H3: Experience and Intention to Adopt **Hypothesis 3 (H3):** ***Individuals with prior experience with social robots demonstrate a higher intention to adopt than those without prior experience.***	H1a: Assistant frame → positive adoption intention H1b: Innovation frame → positive adoption intention H1c: Companion frame → positive adoption intention H1d: Gimmick frame → negative adoption intention H1e: Threat frame → negative adoption intention	**Diffusion of Innovations - Trialability** (Rogers, 2003, p. 16; see Section 2.3.2). Adoption in HE contexts: Sahin, 2006, p. 14; Rudolph et al., 2016, pp. 5-6 (see Section 2.3.4). Prior experience as proxy for trialability → reduces uncertainty and fosters adoption readiness (see Section 2.4).

Source: Own formulation

Table 10 Overview of Hypotheses, Empirical Results, and Conclusions

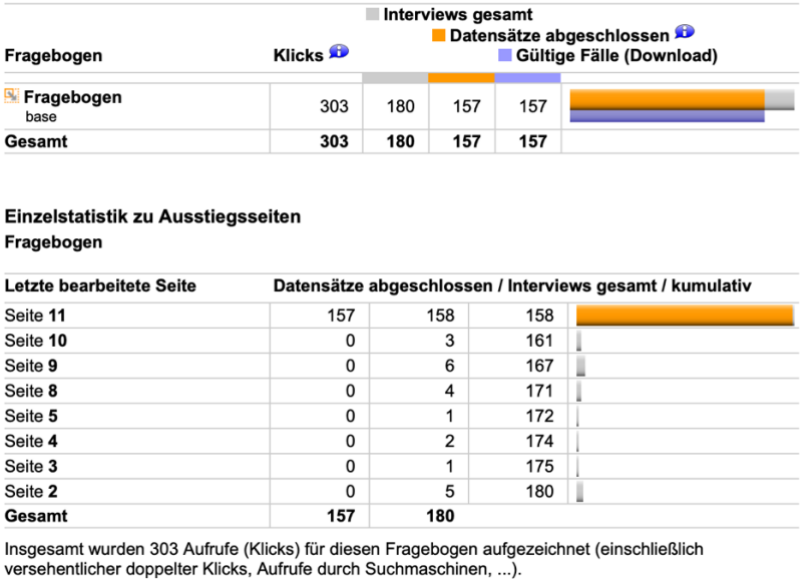
Hypothesis	Statement	Result (ρ / β / U)	Conclusion
H1a (Assistant)	Assistant frame is positively associated with adoption intention	$\rho = .831$, $p < .001$	Supported (strong positive effect)
H1b (Innovation)	Innovation frame is positively associated with adoption intention	$\rho = .611$, $p < .001$	Supported (strong positive effect)
H1c (Companion)	Companion frame is positively associated with adoption intention	$\rho = .372$, $p < .001$	Supported (moderate positive effect)
H1d (Gimmick)	Gimmick frame is negatively associated	$\rho = -.571$, $p < .001$	Supported (strong negative effect)

	with adoption intention		
H1e (Threat)	Threat frame is negatively associated with adoption intention	ρ = .099, p = .225	Not supported (no effect)
H2a (Relative Advantage)	Relative Advantage is positively associated with adoption intention	ρ = .846, β = .599, p < .001	Supported (very strong predictor)
H2b (Compatibility)	Compatibility is positively associated with adoption intention	ρ = .854, β = .460, p < .001	Supported (very strong predictor)
H2c (Ease of Use)	Ease of Use is positively associated with adoption intention	ρ = .459, p < .001; β n.s.	Partially supported (bivariate only)
H2d (Trialability)	Trialability is positively associated with adoption intention	ρ = .139, p = .096	Not supported
H2e (Observability)	Observability is positively associated with adoption intention	ρ = .561, p < .001; β = -.195, p = .001	Not supported (negative in regression)
H2f (Image)	Image is positively associated with adoption intention	ρ = .205, p = .012; β = -.216, p < .001	Not supported (negative in regression)
H2g (Voluntariness)	Voluntariness is positively associated	ρ = .227, p = .005; β n.s.	Partially supported (weak bivariate only)

	with adoption intention		
H2h (Visibility)	Visibility is positively associated with adoption intention	$\rho = .373$, $p < .001$; $\beta = .216$, $p < .001$	Supported (moderate predictor)
H3 (Experience)	Prior experience increases adoption intention	$U = 544.50$, $Z = -7.07$, $p < .001$; Mean rank: 121.28 vs. 63.65	Supported (strong effect)

Source: Own formulation

Appendix E: Survey Completion Statistics (SoSci Survey)



Interviews gesamt
Datensätze abgeschlossen
Gültige Fälle (Download)

Fragebogen	Klicks			
Fragebogen base	303	180	157	157
Gesamt	**303**	**180**	**157**	**157**

Einzelstatistik zu Ausstiegsseiten
Fragebogen

Letzte bearbeitete Seite	Datensätze abgeschlossen	Interviews gesamt	kumulativ
Seite **11**	157	158	158
Seite **10**	0	3	161
Seite **9**	0	6	167
Seite **8**	0	4	171
Seite **5**	0	1	172
Seite **4**	0	2	174
Seite **3**	0	1	175
Seite **2**	0	5	180
Gesamt	**157**	**180**	

Insgesamt wurden 303 Aufrufe (Klicks) für diesen Fragebogen aufgezeichnet (einschließlich versehentlicher doppelter Klicks, Aufrufe durch Suchmaschinen, ...).

Figure 16 Survey Completion Statistics

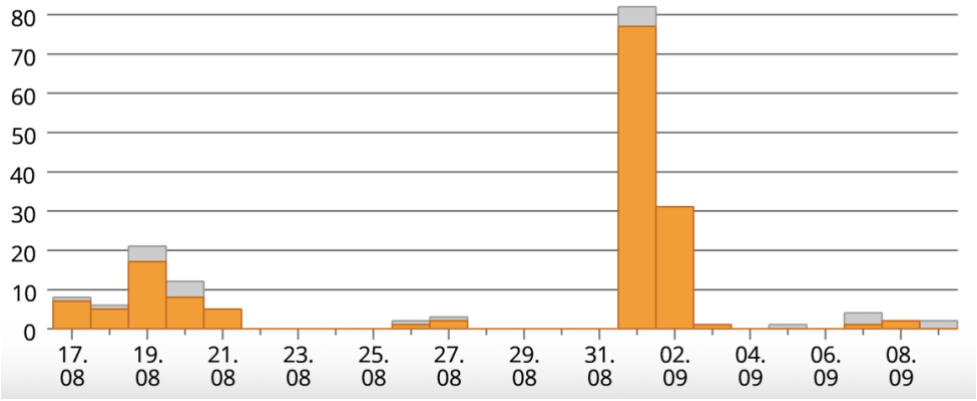


Figure 17 Survey Time Frame

Appendix F: SPSS Output Tables

Source: Own survey data, analysis with IBM SPSS Statistics

Table 11 Current Role of Respondents

CurrentRole

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Student	153	97.5	97.5	97.5
	Professor / Lecturer	2	1.3	1.3	98.7
	Research staff	2	1.3	1.3	100.0
	Total	157	100.0	100.0	

Source: Own survey data, analysis with IBM SPSS Statistics

Table 12 Distribution of Respondents by Field of Study/Discipline

field

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Natural Sciences (e.g., Biology, Chemistry, Physics, Mathematics)	13	8.3	8.3	8.3
	Engineering / Technology (e.g., Mechanical, Electrical, Computer Science, IT)	22	14.0	14.0	22.3
	Social Sciences (e.g., Sociology, Psychology, Political Science)	27	17.2	17.2	39.5
	Business / Management / Marketing	33	21.0	21.0	60.5
	Economics	28	17.8	17.8	78.3
	Education / Pedagogy	15	9.6	9.6	87.9
	Humanities (e.g., Philosophy, History, Languages, Literature)	7	4.5	4.5	92.4
	Medicine and Health (e. g., Medicine, Nursing, Public Health)	4	2.5	2.5	94.9
	Law / Legal Studies	3	1.9	1.9	96.8
	Art / Design / Media	4	2.5	2.5	99.4
	Interdisciplinary / Applied Sciences	1	.6	.6	100.0
	Total	157	100.0	100.0	

Source: Own survey data, analysis with IBM SPSS Statistics

Table 13 Age of Respondents

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Under 24	88	56.1	56.1	56.1
	25?34	52	33.1	33.1	89.2
	35?44	13	8.3	8.3	97.5
	45?54	4	2.5	2.5	100.0
	Total	157	100.0	100.0	

Source: Own survey data, analysis with IBM SPSS Statistics

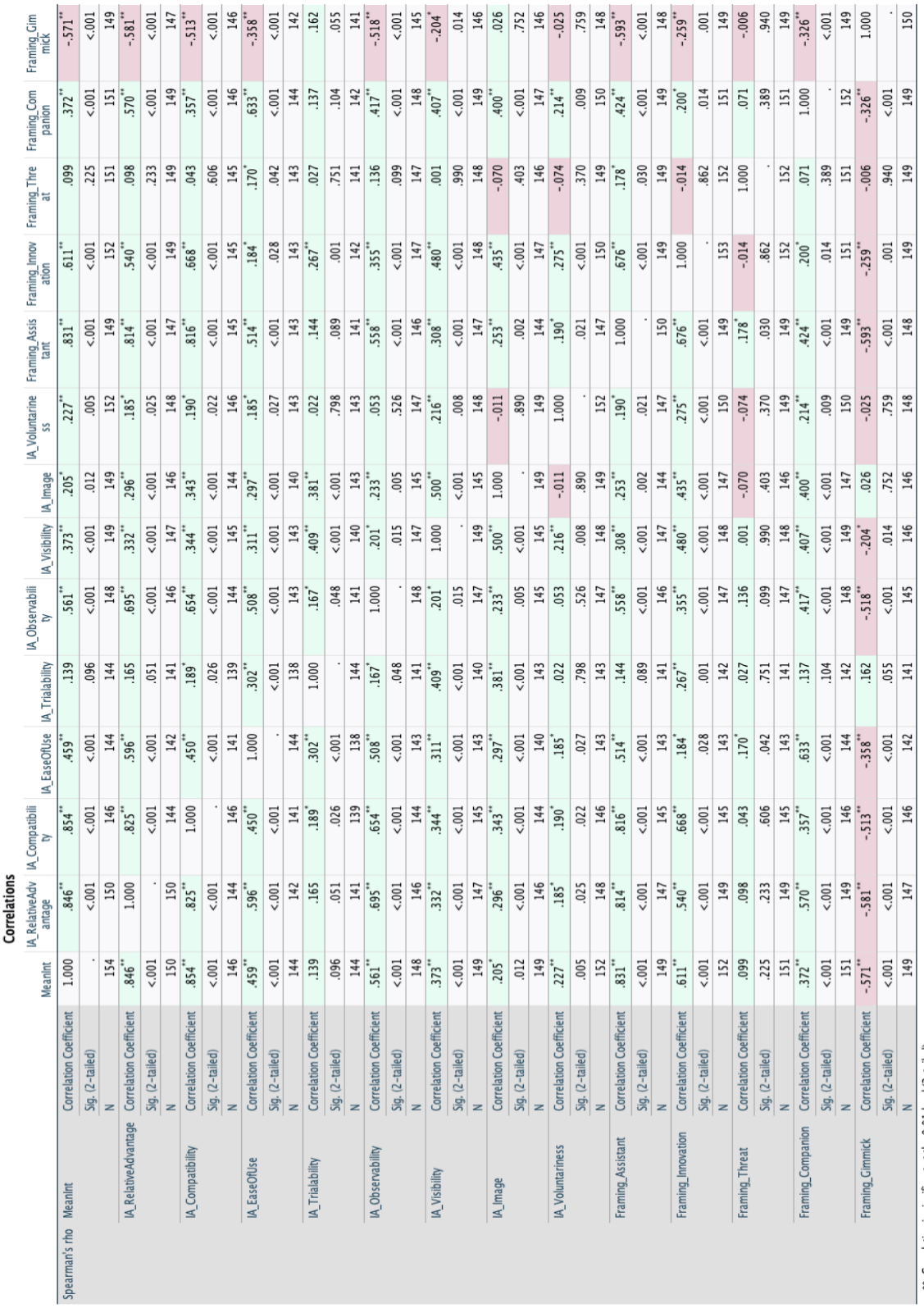
Table 14 Prior Interaction Experience with Social Robots

Interaction 1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	38	24.2	24.2	24.2
	No	119	75.8	75.8	100.0
	Total	157	100.0	100.0	

Source: Own survey data, analysis with IBM SPSS Statistics

Table 15 Spearman's rank-order correlations between framing variables and innovation



Correlations

			MeanInt	IA_RelativeAdvantage	IA_Compatibility	IA_EaseOfUse	IA_Trialability	IA_Observability	IA_Visibility	IA_Image	IA_Voluntariness	Framing_Assistant	Framing_Innovation	Framing_Threat	Framing_Companion	Framing_Gimmick
Spearman's rho	MeanInt	Correlation Coefficient	1.000	.846**	.854**	.459**	.139	.561**	.373**	.205*	.227**	.831**	.611**	.099	.372**	-.571**
		Sig. (2-tailed)	.	<.001	<.001	<.001	.096	<.001	<.001	.012	.005	<.001	<.001	.225	<.001	<.001
		N	154	150	146	144	144	148	149	149	152	149	152	151	151	149
	IA_RelativeAdvantage	Correlation Coefficient	.846**	1.000	.825**	.596**	.165	.695**	.332**	.296**	.185*	.814**	.540**	.098	.570**	-.581**
		Sig. (2-tailed)	<.001	.	<.001	<.001	.051	<.001	<.001	<.001	.025	<.001	<.001	.233	<.001	<.001
		N	150	150	144	142	141	146	147	146	148	147	149	149	149	147
	IA_Compatibility	Correlation Coefficient	.854**	.825**	1.000	.450**	.189*	.654**	.344**	.343**	.190*	.816**	.668**	.043	.357**	-.513**
		Sig. (2-tailed)	<.001	<.001	.	<.001	.026	<.001	<.001	<.001	.022	<.001	<.001	.606	<.001	<.001
		N	146	144	146	141	139	144	145	144	146	145	145	145	146	146
	IA_EaseOfUse	Correlation Coefficient	.459**	.596**	.450**	1.000	.302**	.508**	.311**	.297**	.185*	.514**	.184*	.170*	.633**	-.358**
		Sig. (2-tailed)	<.001	<.001	<.001	.	<.001	<.001	<.001	<.001	.027	<.001	.028	.042	<.001	<.001
		N	144	142	141	144	138	143	143	140	143	143	143	143	144	142
	IA_Trialability	Correlation Coefficient	.139	.165	.189*	.302**	1.000	.167*	.409**	.381**	.022	.144	.267**	.027	.137	.162
		Sig. (2-tailed)	.096	.051	.026	<.001	.	.048	<.001	<.001	.798	.089	.001	.751	.104	.055
		N	144	141	139	138	144	141	140	143	143	141	142	141	142	141
	IA_Observability	Correlation Coefficient	.561**	.695**	.654**	.508**	.167*	1.000	.201*	.233**	.053	.526**	.355**	.136	.417**	-.518**
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	.048	.	.015	.005	.526	<.001	<.001	.099	<.001	<.001
		N	148	146	144	143	141	148	147	145	147	146	147	147	148	145
	IA_Visibility	Correlation Coefficient	.373**	.332**	.344**	.311**	.409**	.201*	1.000	.500**	.216**	.308**	.480**	.001	.407**	-.204*
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	.015	.	<.001	.008	<.001	<.001	.990	<.001	.014
		N	149	147	145	143	140	147	149	145	148	147	148	148	149	146
	IA_Image	Correlation Coefficient	.205*	.296**	.343**	.297**	.381**	.233**	.500**	1.000	-.011	.253**	.435**	-.070	.400**	.026
		Sig. (2-tailed)	.012	<.001	<.001	<.001	<.001	.005	<.001	.	.890	.002	<.001	.403	<.001	.752
		N	149	146	144	140	143	145	145	149	149	144	147	146	147	146
	IA_Voluntariness	Correlation Coefficient	.227**	.185*	.190*	.185*	.022	.053	.216**	-.011	1.000	.190*	.275**	-.074	.214**	-.025
		Sig. (2-tailed)	.005	.025	.022	.027	.798	.526	.008	.890	.	.021	<.001	.370	.009	.759
		N	152	148	146	143	143	147	148	149	152	147	150	149	150	148
	Framing_Assistant	Correlation Coefficient	.831**	.814**	.816**	.514**	.144	.558**	.308**	.253**	.190*	1.000	.676**	.178*	.424**	-.593**
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	.089	<.001	<.001	.002	.021	.	<.001	.030	<.001	<.001
		N	149	147	145	143	141	146	147	144	147	150	149	149	149	148
	Framing_Innovation	Correlation Coefficient	.611**	.540**	.668**	.184*	.267**	.355**	.480**	.435**	.275**	.676**	1.000	-.014	.200*	-.259**
		Sig. (2-tailed)	<.001	<.001	<.001	.028	.001	<.001	<.001	<.001	<.001	<.001	.	.862	.014	.001
		N	152	149	145	143	142	147	148	147	150	149	153	152	151	149
	Framing_Threat	Correlation Coefficient	.099	.098	.043	.170*	.027	.136	.001	-.070	-.074	.178*	-.014	1.000	.071	-.006
		Sig. (2-tailed)	.225	.233	.606	.042	.751	.099	.990	.403	.370	.030	.862	.	.389	.940
		N	151	149	145	143	141	147	148	146	149	149	152	152	151	149
	Framing_Companion	Correlation Coefficient	.372**	.570**	.357**	.633**	.137	.417**	.407**	.400**	.214**	.424**	.200*	.071	1.000	-.326**
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	.104	<.001	<.001	<.001	.009	<.001	.014	.389	.	<.001
		N	151	149	146	144	142	148	149	147	150	149	151	151	152	149
	Framing_Gimmick	Correlation Coefficient	-.571**	-.581**	-.513**	-.358**	.162	-.518**	-.204*	.026	-.025	-.593**	-.259**	-.006	-.326**	1.000
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	.055	<.001	.014	.752	.759	<.001	.001	.940	<.001	.
		N	149	147	146	142	141	145	146	146	148	148	149	149	149	150

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Source: Own survey data, analysis with IBM SPSS Statistics

Declaration of Originality

I hereby confirm that I have written this work independently and have used no sources other than those indicated nor aids other than those permissible, and have appropriately declared all citations.

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Mülheim a. d. Ruhr, 23.09.2025

Faber Irina

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