The International Journal of Business Management and Technology, Volume 10 Issue 02 February 2026
ISSN: 2581-3889

Research Article Open Access

A Conceptual Model for Human-Centric AI Adoption in Manufacturing Projects: Integrating Socio-Technical Systems Theory and Technology Acceptance Model

Domagoj Mihaljevic
Alma Mater Europaea University, Slovenska ulica 17, 2000 Maribor, Slovenia, EU

Abstract: The growing implementation of Artificial Intelligence (AI) into manufacturing settings is transforming project management practices but uptake is still somewhat uneven and theoretically disjointed. Current studies focus on AI implementation mainly on a technical systems capture or an individual-level technology acceptance model, which leads to a constrained comprehension of the interplay between organisational, technological, and human aspects in a project-based environment. In response to this gap, this paper presents a new conceptual model, which combines the Socio-Technical Systems (STS) theory with the Technology Acceptance Model (TAM) in explaining the use of Human-Centred AI (HCAI) in manufacturing projects. This model proposes a multi-level model whereby social subsystem variables (organisational readiness, leadership support, and team capability) and technical subsystem variables (transparency, compatibility, and data infrastructure quality) affect cognitive mediators, which include, perceived usefulness, perceived ease of use, and trust in AI, which, in turn, lead to adoption behaviour and project performance outcomes. The contextual moderators suggested to influence the adoption performance relationship are project complexity and formal integration mechanisms. The research has added to the theory by closing a gap between socio-technical alignment on a macro-level and acceptance mechanisms at a micro-level and expanded TAM by expressly considering the principles of trust and human-centric AI. In practical sense, the framework provides an organised diagnostic and implementation tool to organisations and project management offices intending to match the technological capabilities with human and organisational preparedness. The paper highlights the fact that sustainable AI-based performance gains require human-centred design, which is interwoven into consistent socio-technical systems by focusing on transparency, augmentation, and joint optimisation.

Keywords: Human-Centred Artificial Intelligence, Manufacturing Projects, Project Management, Socio-Technical Systems, Technology Acceptance Model

I. INTRODUCTION AND BACKGROUND

Digital technologies and specifically Artificial Intelligence (AI) are transforming the manufacturing industry dramatically, changing the way production systems and the decision-making process operate, and the design and structure of organisations. The Industry 4.0 to Industry 5.0 is a transition of an entirely automation-focused efficiency towards a more human-centred paradigm focusing on the collaboration between people and intelligent machines (Industry 4.0; Industry 5.0). Whereas Industry 4.0 is about cyber-physical systems, data integration, and automation (Lee et al., 2020; Kang et al., 2016), Industry 5.0 brings in the human-centricity notion, in which technological systems are created to enhance human aptitudes, but not to unfamiliarised them (Nahavandi, 2019; Romero et al., 2021).

The advent of Industry 4.0 was a paradigm shift to intelligent and interconnected manufacturing systems that are cyber-physically integrated, have smart factories, and are able to communicate in real time (Zhou et al., 2015). This change focused on automation, digitisation, and optimisation of operations. The fundamental technological enablers were cyber-physical, industrial internet architecture, and data-driven control (Lee et al., 2020; Kang et al., 2016). Although these changes greatly improved productivity and visibility of processes, they also added complexity to the systems and there were also some concerns with workforce displacement and too much technological determinism.

With the maturation of the technological basis of Industry 4.0, shortcomings of automation-related paradigms became more pronounced. These issues have led to Industry 5.0, that reinvents the human in the intelligent production systems and prioritises the collaboration between humans and machines over replacement (Nahavandi, 2019; Romero et al., 2021).

The digital transformation as represented by Industry 5.0, focuses on resilience, sustainability, and human empowerment, in addition to efficiency gains.

AI technologies are the centre of this change through facilitating higher abilities, including predictive analytics, intelligent automation, and real-time decision support. In the manufacturing industry, AI has also proven to be highly promising in streamlining production, quality control, and operational efficiency based on the data-driven insights (Tao et al., 2018; Wang et al., 2022). Nonetheless, even though these technological improvements exist, the effective use of AI is not only a technical issue but also a socio-organisational one, and there should be harmony between human, organisational, and technological factors (Mariani et al., 2023).

This is a change in the human-centred AI and the need to develop systems that are transparent, explainable, and human-value oriented (Shneiderman, 2020; Dignum, 2019). This view is consistent with the idea of hybrid intelligence, according to which man and AI systems complement each other (Jarrahi et al., 2022). Consequently, to gain insight into AI adoption, one must go beyond strictly technical standpoints and look at socio-technical complexities whereby one looks at the capabilities of the system and human interaction processes within that framework.

Furthermore, international governance structures focus on the fact that AI systems should be capable of guaranteeing transparency, accountability, and human supervision to enable the adoption of AI in a responsible manner (UNESCO, 2021). Recent Industry 5.0 studies emphasise the significance of human-AI collaboration architectures that are organised in the way that facilitates efficient industrial decision-making (Tóth et al., 2023).

1.1 AI in Manufacturing Project Management

Although the use of AI has been extensively researched in the context of operational manufacturing processes, the use of the technology in manufacturing project management is not yet well-researched. Projects in manufacturing, including the creation of new products, the digital transformation, and upgrades to a production system are temporary, complex, and intricate projects that are strict in terms of time, cost, and scope (Turner and Miterev, 2019).

In this regard, AI brings enormous possibilities in improving the practice of project management. The applications being developed are AI-based optimisation of many processes, prediction of risks, cost forecasting, and decision support systems that help to make the plan more accurate and less uncertain (Wang et al., 2022; Tao et al., 2018). These tools can help revolutionise the previous tools of project management, with the ability to make more flexible and data-driven decisions.

Nevertheless, there are some peculiar challenges associated with the implementation of AI within project settings. In contrast to the standard production processes, projects are dependent on human judgment, teamwork, and dynamic decision-making. Consequently, the implementation of AI into the project environments depends not just on technological potentials, but also on human elements, namely trust, usability, and perceived value (Jarrahi, 2018; Raisch & Krakowski, 2021). This is where the necessity of frameworks considering not only the technical aspect of AI implementation in a project-based setting but also the social aspect lies.

1.2 Problem Statement

Although AI is seen as a promising technology to be used in the manufacturing sector, its usage in project management context is still sparse and uneven. Another issue is that the human aspect of AI integration, specifically, the issues of trust, transparency, and user acceptance, is one of the primary challenges. Studies indicate that people are hesitant to trust AI systems in cases where they feel that they are obscure or not understandable (Glikson and Woolley, 2020; Siau and Wang, 2018). This problem is also worsened by the absence of explainability in AI models that suppresses user confidence and makes it impossible to effectively use them (Gunning et al., 2019; Ribeiro et al., 2016).

Besides the issues that relate to trust, the organisational resistance and lack of readiness to adopt AI are also the major obstacles. Staff members might feel that AI is actually threatening their jobs and therefore resist and engage less

(Parasuraman and Riley, 1997). Moreover, the lack of systematic methods of implementing AI into the current processes may lead to the lack of correlation between the technological potential and business requirements.

One of the basic problems that lie behind such obstacles is the lack of coherence of current research. The existing literature is inclined to analyse the adoption of AI in terms of technical aspects (system performance and algorithms) or in terms of behavioural aspects (individual acceptance and attitudes) (Davis, 1989; Venkatesh et al., 2003). This division

restricts the possibility of a comprehensive comprehension of intricate relationships amid human, organisational, and technological elements in AI adoption.

1.3 Contributions of the Study

This research study contributes to both theory and practice in a variety of ways.

Firstly, theoretically, it provides an advance in the existing literature as it incorporates the Socio-Technical Systems theory with technology acceptance models into an integrated model. This part offers a deeper look into the issue of AI adoption when trying to connect macro-level organisation factors with the micro-level perceptions of individuals.

Second, the research base adds to the developing sphere of human-centred AI, as it incorporates the concepts of transparency, explainability, and trust in the study of the technology uptake. In this way, it can bring traditional models of acceptance closer to the peculiarities of AI systems.

Third, the study also makes some contextual contributions in the sense that it specifically examines the manufacturing project environment that has been significantly neglected in the previous study. This special attention emphasises the unique problems and opportunities of AI implementation in temporary, complicated, and dynamic environments.

Lastly, in the real world, the suggested model provides a systematic structure of organisations that aim to apply AI in project management. It determines major success factors in successful adoption and gives an idea on how organisations can match technological capabilities with human and organisational factors to deliver better project results.

II. LITERATURE REVIEW

2.1 Socio-Technical Systems (STS) Theory

The Socio-Technical Systems (STS) theory presents a theoretical background through which the relationship between human and technological factors in the organisational practices can be identified. Starting with Trist and Bamforth (1951), STS was developed as a result of observing empirically in British coal mines that with mechanisation, not only the productivity, but also social forms, communication patterns and satisfaction levels of the workers changed. They proved that technological optimisation per se was not able to guarantee better results but the result of organisations was based on how the social arrangements and the technical systems were matched. This observation led to the development of a principle of joint optimisation that has been the main focus of STS theory.

The joint optimisation principle assumes that organisations are interdependent systems that consist of a social subsystem and a technical subsystem. The improvements in performance do not take place by means of individual improvement in either of the subsystems but through the way the two subsystems are coordinated and how they adjust to each other (Clegg, 2000). Recent studies support this view and prove that the adoption of AI is affected by the congruency of technological, organisational, and social aspects instead of technical optimisation alone (Mariani et al., 2023). That is, the implementation of new and sophisticated technologies without adjusting the roles and skills, and cultural values can create inefficiencies or opposition. On the other hand, high social cohesion in the absence of proper technological backing could reduce productivity increment.

Social subsystem refers to items like the organisational culture, leadership patterns, communication frameworks, and the ability of the workforce. New technologies are understood and adopted in a certain way by culture. Under conditions of learning orientation and the assistance of innovation, the employees can see the AI as a chance to upgrade skills, instead of being threatened. Leadership is important to put technological change into perspective, explain its purpose, and promote psychological safety. Empirical studies of organisational preparedness focus on the fact that collective commitment and mutual belief in the possibility of change are also vital factors in determining technology adoption results

(Weiner, 2009). On the same note, Armenakis et al. (1993; 2009) claim that preparedness to change is conditioned on the basis of effective communication and engagement of workforce.

Another typical aspect of the social subsystem is skills and competencies. This idea is further developed by the notion of hybrid intelligence, which suggests that healthy systems are created when human and AI abilities are interacting with each other via mutual enhancement (Jarrahi et al., 2022). To be successful in the implementation of AI, technical skills are not a sufficient requirement, cognitive flexibility, and cross-disciplinary cooperation are also needed.

With the transformation of manufacturing systems to the human-AI symbiosis, employees should be able to master the ability to consider the results of algorithms and apply them in decision-making (Jarrahi, 2018). High-grade AI systems will not be used to their full capacity without adequate skill match.

The technical subsystem on the other hand entails the tools, infrastructures, processes and technologies that serve organisational goals. As per recent research, data-centric architectures are vital in AI performance in manufacturing settings, and data quality and governance both are crucial factors (Mudgal, 2025). Within the framework of AI-based manufacturing, machine learning models, data structures, physical and physical systems, and decision support platforms are the components of this subsystem (Lee et al., 2020; Tao et al., 2018). The technical features of reliability of the system, transparency and capability to integrate affect the embedding of AI in the workflows. Notably, the patterns of interaction with the users are influenced by the technical design decisions, which subsequently influence adoption.

The social subsystem and technical subsystem interaction are very acute in project settings. This has resulted in the creation of formal human-AI collaboration architectures that introduce explicit human and technical aspects into industrial systems (Tóth et al., 2023). The manufacturing projects are short-lived, cross-functional, and changing requirements as well as strict coordination requirements (Turner & Miterev, 2019). Implementation of AI tools in these settings changes the power of decisions, communication patterns, and allocation of work. The failure to recognise team dynamics and leadership structures could lead to misalignment and reduce the performance of the project in case AI systems are introduced. Thus, STS theory can be used to offer a macro-level approach to AI adoption as a systemic process, as opposed to a technocratic implementation.

Nonetheless, STS theory is useful in explaining both structural alignment and organisational design but does not provide much information on the psychological processes involved in the individual acceptance of AI technologies. In order to cover this gap, technology acceptance models offer complementary micro-level explanatory power.

2.2 Technology Acceptance Models (TAM / UTAUT)

Technology Acceptance Model (TAM) theory is one of the most dominant theories to explain the adoption of information systems by the user. Initially advanced by Davis (1989), TAM assumes that there are two fundamental beliefs that decide technology adoption and these are perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness is a measure of the perceived level of an individual that the use of a system improves job performance whereas perceived ease of use is the perceived level of the avoidance of effort by the use of a system. Such beliefs determine the attitudes towards technology that in turn affect behavioural intention and usage.

TAM has been widely tested in organisational settings with strong predictive ability. The perceived usefulness in AI-enabled manufacturing settings can be in the form of beliefs that predictive scheduling enhances the accuracy of planning or the belief that AI-based analytics minimises errors. Perceived ease of use can be associated with a user-friendly interface or compatibility with the working processes. Notably, the concept of TAM models adoption as a cognitive appraisal process due to performance expectations and consideration of effort.

TAM has been extended subsequently in its explanatory scope. Unified Theory of Acceptance and Use of Technology (UTAUT) is a synthesis of earlier theories which implies the appearance of new constructs like social influence and facilitating conditions (Venkatesh et al., 2003). Social influence indicates how much people believe that significant others feel that they ought to use the system. Facilitating conditions refer to how organisational and technical systems favour system use. Subsequent modifications, such as TAM3, use experience, anxiety, and intervention processes (Venkatesh & Bala, 2008).

Such extensions are especially applicable to project settings where peer approval and management support have a strong influence on the adoption process.

The social influence in cross-functional teams can make the difference between the AI recommendations being perceived as authoritative input and optional suggestions. Facilitating conditions such as training and infrastructure preparedness, make it easier to use barriers.

Technology acceptance models are somewhat limited in spite of the strengths. To begin with, they mostly work at the individual level and extensively abstract with the larger organisational structures.

Although constructs like facilitating conditions take into consideration the contextual factors, TAM fails to theorise the role of socio-technical arrangements in influencing user perceptions. Second, the conventional acceptance models have been formulated under moderately stable information systems rather than adaptive AI technologies, which have algorithmic opacities and learning abilities.

AI systems create an increment of complexity due to their possibility of providing outputs that are both probabilistic and non-deterministic. The usefulness of AI can be perceived not only based on performance results but also based on the trust in algorithmic arguments. Automation studies show that improper dependence or insufficient dependence may arise when users have incorrect system assumptions (Parasuraman et al., 2000). Thus, AI needs to be accepted taking into account additional factors outside the scope of effort and performance expectancy.

Furthermore, TAM is silent regarding problems of explainability, transparency, or ethical alignment, which have become the dimensions that are considered to be the essential ones in the context of AI usage (Gunning et al., 2019; Shneiderman, 2020). Explainability has been proposed to be a key to user trust and successful use of AI, especially in more complex systems (Arrieta et al., 2020). Moreover, AI systems should be transparent, accountable, and human controlled, which is a priority in global governance systems (UNESCO, 2021). Therefore, although TAM will be informative about the cognitive determinants of use, it needs to be enriched with theories to be able to explain the peculiarities of AI systems involving human interactions.

2.3 Human-Centred AI (HCAI)

Human-Centred Artificial Intelligence (HCAI) has become a reaction to fears of foggy, autonomous systems of AI that exclude human agency. HCAI also focuses on creating AI technologies that are understandable, responsible, and focused on human values (Shneiderman, 2020; Dignum, 2019). The latest policy frameworks only support the idea that human values, fairness, and accountability should be incorporated into AI systems across their lifecycle (UNESCO, 2021). HCAI does not call to complete automation, but promotes augmentation, as a way of supporting human decision-making without losing oversight and control. This can be compared to the automation-augmentation paradox that emphasises the importance of striking a balance between increasing efficiency and creating human value (Raisch and Krakowski, 2021).

As an essential tenet of HCAI, explainability. Explainable AI methods intend to solve the lack of transparency of complex models by ensuring their decision-making process is discernible by their users (Arrieta et al., 2020). Most AI systems, especially deep learning systems, are black boxes, meaning that they produce results without a mechanism that can be interpreted as logic. Explainable AI (XAI) is aimed at developing information on the logic of models to improve the understanding of the user (Gunning et al., 2019). It is possible to use techniques like local explanation models to help the user explain why certain predictions occurred (Ribeiro et al., 2016). The author of this article, Rai (2020) frames this change so as to shift to the black box to the glass box systems wherein the user confidence is reinforced by transparency.

Transparency is not necessarily limited to technical interpretability, but it also includes clarity of system goals, data use and limits of decision making. Ethical models such as accountability, fairness, and responsibility are highlighted in the implementation of AI (Floridi et al., 2018; Jobin et al., 2019). Recent studies also emphasise the fact that the quality of AI systems is determined essentially by the quality and ethical validity of training data (Hagendorff, 2021). According to Dignum (2019), building responsible AI involves the correspondence of the system design process with the values of the society.

These dimensions have a direct impact on trust that acts as a mediating factor between system characteristics and adoption behaviour. Trust in AI is an attitude of a user to using the results of an algorithmic output in the case of uncertainty (Glikson and Woolley, 2020). Empirical evidence shows that transparency and reliability perceived increase trust, whereas the opposite is true regarding the lack of these principles (Siau and Wang, 2018). Trust is inevitable in the setting of projects where the decisions undertaken have financial and operational implications.

Human augmentation also makes HCAI different to automation-focused paradigms. Hybrid type of intelligence also focuses more on the synergistic usage of human and AI capabilities (Jarrahi et al., 2022). Instead of substituting human judgment, AI systems will be developed to supplement expertise to achieve hybrid intelligence (Jarrahi, 2018).

This method is in line with the focus on collaborative human-AI systems provided by Industry 5.0 (Nahavandi, 2019; Romero et al., 2021). Industry 5.0 also directly facilitates human-centered, sustainable, and resilient industrial systems (Breque et al., 2021). Organisations can alleviate resistance and improve acceptability by referring to AI as a supportive resource and not a replacement.

The notion of the so-called smart operator is implemented in smart factory settings and focuses on developing human capabilities with the help of smart assistance systems instead of eliminating human proficiency (Longo et al., 2017). This view is very much close to the human-centred AI ideologies, which regard technology as an augmenting ability. AI systems can enhance the quality of performance by the operators without replacing the human agency by enhancing the quality of their situational awareness, accuracy of decisions, and cognitive support. This type of augmentation mechanism enhances engagement and minimises resistance, which builds trust and long-term dependence.

HCAI therefore proposes significant constructs such as explainability, transparency, accountability and augmentation that are an extension of the old technology acceptance models. Nevertheless, incorporation of these principles in formal adoption structures is low especially in manufacturing project settings.

2.4 AI in Manufacturing Projects

AI uses in manufacturing projects have been related to predictive scheduling, risk forecasting, cost approximating and real-time decision support. Predictive analytics have the potential of predicting resource bottlenecks and optimise tasks sequencing to enhance schedule compliance (Tao et al., 2018). Machine learning models are used to predict risks and contingency planning by analysing past data (Wang et al., 2022). All these capabilities hold a great potential in improving project performance.

However, the issues of integration remain. Problems associated with data like heterogeneity and system integration have a great importance on the application of AI in the manufacturing setting (Mudgal, 2025). The AI systems have to connect with old systems and nonhomogeneous data sources, which makes the process more challenging (Lee et al., 2020). Also, project teams can be reluctant to accept algorithmic proposals that can be seen as too invasive or not consistent with experiential judgment (Parasuraman and Riley, 1997). The automation-augmentation paradox, in accordance with which people can view AI not as a supportive device but as a threat, can explain this resistance (Raisch and Krakowski, 2021). In temporary teams where understanding has not yet solidified, resistance can be increased.

Furthermore, projects are high uncertainty projects so interpretability and trust become even more critical. According to the empirical research, socio-technical aspects and the capabilities of innovation play a significant role in smart manufacturing adoption (Pan et al., 2024). AI outputs can be discounted without proper clarification and explanation: organisational readiness, leadership approval, and training quality affect the adoption of AI tools into the project processes.

Therefore, AI implementation in manufacturing projects cannot be explained only with the help of technical performance measures. It needs to have an all-encompassing framework that takes into consideration socio-technical harmony, personal acceptance processes, and humanistic design ideals.

III. RESEARCH GAP AND RESEARCH QUESTION

3.1 Research Gap

Despite the significant advancements in the comprehension of artificial intelligence technologies and their acceptance by users, there is a significant gap in terms of socio-technical and behavioural approaches. The Socio-Technical Systems (STS) theory focuses on the co-optimisation of both the social and technical subsystems as a precondition of successful organisational functioning (Trist and Bamforth, 1951; Clegg, 2000). Nevertheless, STS has been mostly used at the macro level and the mechanisms of how individuals develop technology adoption beliefs have not been explicitly modeled.

Other technology acceptance models like the TAM and the UTAUT however concentrate on individual level determinants of adoption specifically the perceived usefulness and perceived ease of use (Davis, 1989; Venkatesh et al., 2003). Although the models are very powerful in explaining the phenomenon at the psychological level alone, they consider the organisational structures and technological configurations as part of the contextual background factors as opposed to mutually reinforcing subsystems.

Although these two views are conceptually complementary, the two perspectives have seldom been combined into a single concept, especially in the environment of human-centred AI in manufacturing projects. Consequently, the current body of literature is not in a position to provide a complete explanation of how the socio-technical configurations influence individual perceptions and how these perceptions are converted to project-level performance outcomes.

Moreover, studies that specifically cover AI adoption when it comes to manufacturing project situations are few. Projects are time-bound, multi-faceted and uncertain settings where teamwork and judgment are at the centre stage. The new idea of human-centred AI, which focuses on transparency, explainability, accountability, and augmentation (Floridi et al., 2018; Jobin et al., 2019; Passalacqua et al., 2024), further contributes to the necessity to integrate frameworks that would combine technical design with organisational alignment and individual acceptance mechanisms.

3.2 Research Objective and Research Question

The main aim of this study in relation to this gap is to formulate a conceptual model to help bridge this gap by incorporating the theory of Socio-Technical Systems (STS) with TAM/UTAUT to understand how to attain the adoption of human-centred AI in manufacturing project management.

The study, in particular, intends to determine the impact of socio-technical factors, including organisational readiness, leadership support, team capability, and AI system characteristics, on individual perceptions, including perceived usefulness, perceived ease of use, and trust, which subsequently affect the adoption behaviour and project performance outcomes.

The guiding research question of the present study is, therefore, as follows: How socio-technical factors affect the adoption of human-centred AI in the manufacturing project management, and how the adoption of human-centred AI impacts project performance outcomes?

IV. CONCEPTUAL MODEL DEVELOPMENT

4.1 Rationale for Integrating STS and TAM

Such combination of the Socio-Technical Systems (STS) theory with Technology Acceptance Models (TAM/UTAUT) will directly serve the purpose of the fragmentation of current studies on technology adoption in complex organisational settings. STS theory is a macro-level explanation of organisational performance with the assertion that the effectiveness relies on the integration of social and technical subsystems (Trist and Bamforth, 1951; Clegg, 2000). Organisations are theorised as dependable systems over which culture, leadership, work design, and skill structures interact with technological infrastructures. According to the principle of joint optimisation, neither technological sophistication nor social cohesion can ensure performance, but the results can be attributed to their compatibility.

STS theory does not explicitly conceptualise the cognitive and behavioral processes by which people assess and implement new technologies in spite of its systemic power. It describes structural circumstances but is relatively silent as far as the formation of belief, intention, and individual level use behaviour are concerned. Conversely, TAM has a micro-level pattern of thinking with cognitive estimations. Davis (1989) suggested that attitudes are influenced by perceived usefulness (PU) and perceived ease of use (PEOU) and this will affect behavioural intention and actual use of a system. This was further refined by subsequent models such as UTAUT (Venkatesh et al., 2003) and TAM3 (Venkatesh and Bala, 2008) to provide an increased level of explanatory detail to incorporate social influence, facilitating conditions, and experience-related determinants.

Nevertheless, the development of acceptance models is largely based on the stable information systems environment and usually views the condition of organisations as a background variable instead of the interacting subsystems. They describe the intentions that users develop yet they do not theorise all the way that the socio-technical design influences such perceptions. This is worsened by AI systems. The AI technologies, in contrast to the traditional IT, are associated with probabilistic results, adaptive learning, and algorithmic opacities. These features add to the level of uncertainty and heighten the significance of trust, transparency, and alignment of the system (Gunning et al., 2019; Glikson and Woolley, 2020). Explainability has also been recognised as a key condition to developing trust in AI systems, especially in the contexts that are marked by ambiguity and algorithmic unintelligibility (Arrieta et al., 2020).
Multi-level analysis is also required in the manufacturing project environments. Projects are executed within time constraints, inter-functional team work, and dynamic needs. The decisions to be adopted are made at individual level, but within organisational cultures, leadership structures, and the technological structures and infrastructures. This makes a multi-level structure indispensable. Recent studies also indicate that the adoption of AI should be coordinated on the technological, organisational, and social levels, which supports the need of integrative frameworks (Mariani et al., 2023). STS describes the impact of the macro-level conditions on the technological embedding, and TAM describes how the individual perceptions serve as the translators of the macro-level conditions into the behavioural consequences. By combining the two views, it is possible to provide a consistent explanation of the way the socio-technical set-ups influence cognitive mediators which eventually define the adoption of AI and the success of the project.

4.2 Overview of the Proposed Model

The suggested conceptual model develops a multi-level and chronological rationale between socio-technical variables and project performance outcomes using cognitive mediators and behavioural adoption. The socio-technical factors are based on the STS theory, including socio-technical subsystems. These aspects create the contextual situation according to which AI tools are introduced and interpreted.

The socio-technical factors on the first stage affect three mediators, which are perceived usefulness, perceived ease of use, and trust in AI. True to TAM, PU holds beliefs as to performance improvement, and PEOU to expected effort (Davis, 1989). The aspect of trust is added as one of the essential extensions associated with AI-specific features like explainability and reliability (Siau and Wang, 2018; Glikson and Woolley, 2020). Trust is a cognitive and an affective belief that affects behavioural intention. Transparency and explainability of systems significantly contribute to building trust as users can comprehend and trust the results of algorithms in AI settings (Arrieta et al., 2020).
The second phase is the conceptualisation of intention to use as the proximity of adoption behaviour. Behavioural intention shows how a user is determined to use AI tools in project-related decisions. Adoption is not simply described as access or availability but is a constant dependence on the output of an algorithm as part of the planning, monitoring and controlling processes.

The third stage connects the adoption behaviour with the multidimensional project performance outcomes. Performance includes efficiency in operations, minimisation of mistakes and satisfaction among the stakeholders. Empirical evidence demonstrates that AI-based analytics are more accurate in making predictions and less efficient in manufacturing systems (Tao et al., 2018; Wang et al., 2022). Nevertheless, the mentioned advantages can only be realised when AI tools are proactively integrated into the project processes.

Lastly, the model has moderators that influence the performance-adoption relationship strength. Performance gains may be enhanced or reduced by the complexity of the project, formal integration mechanisms and wider organisational context.

The framework accurately reflects systemic alignment, individual belief formation, and contingencies by organising the model in a sequence, namely, socio-technical antecedents, cognitive mediators, adoption, and outcomes, into a single explanatory framework.

Figure 1 illustrates the integrated conceptual structure as described above. The model shows the multi-level associations between socio-technical variables and cognitive mediators, adoption behaviour and project performance and the moderating contextual conditions that drive performance outcomes.

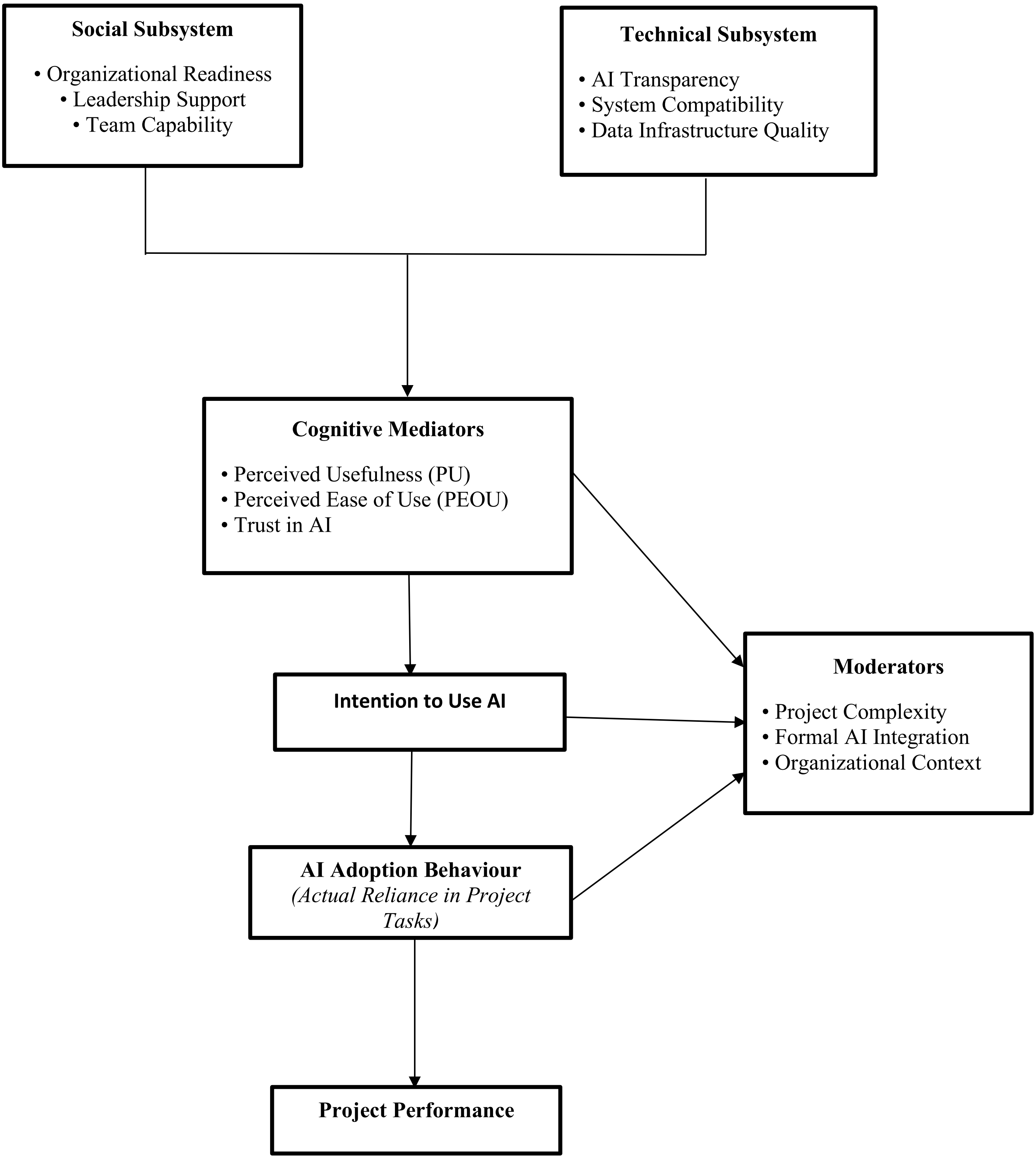

Figure 1. Integrated socio-technical model of human-centric AI adoption in manufacturing projects.

The model connects social and technical subsystem variables with cognitive mediators (perceived usefulness, perceived ease of use, and trust) which affect intention and adoption behaviour, which eventually leads to the project performance outcome. The relationship between performance and formal mechanisms of integration and their organisational context modulate the performance.

Socio-Technical Factors

The socio-technical basis of the model reflects the principle of joint optimisation as described by Trist and Bamforth (1951). When social subsystems and technical subsystems are not optimised independently, it enhances the performance of the organisation. In the manufacturing projects, socio-technical factors can be conceptualised in two mutually dependent levels; the social subsystem elements and the technical subsystem characteristics.

The social subsystem includes the readiness organised, the support of leadership, and the team capability. Organisational readiness can be described as the willingness to change collectively and the feeling of the possibility to change (Weiner, 2009). Readiness determines the degree to which employees consider technological initiatives as valid and viable in the situation of AI adoption. The high preparedness lessens the uncertainty and enhances the formation of positive beliefs about the potential benefits of AI.

The second important factor is leadership support. Technological narratives, allocation, and adoption modeling are all developed by leaders. According to research in change management, it is essential to use persuasive communication and engage employees in building readiness (Armenakis et al., 1993; Armenakis and Harris, 2009). In projects, the visible leadership support can make AI tools legitimate and decrease mistrust.

Team capability encompasses technical proficiency, being data literate and cognitively adaptable. AI systems generate probabilistic suggestions, which can only be interpreted as opposed to being accepted unquestioningly. Hybrid models of intelligence focus on cooperation between human intelligence and algorithmic analytics (Jarrahi, 2018). The teams with analytical competence and skills to work interdisciplinarily have higher chances to convert AI insights into efficient decisions.

The technical subsystem encompasses data infrastructure, transparency and compatibility. Transparency can be understood as the interpretability of AI outputs. Explainable AI focuses on offering an overview of processes through which models make decisions (Gunning et al., 2019; Ribeiro et al., 2016). The open systems support comprehension and build trust.

The adherence of AI tools to the current workflows and processes is the reflection of compatibility. Systems, which fit well into project routines, are not met with a lot of resistance as opposed to those, which need radical redesign. The integration capacity has impacts on the perceived value and usability.

The technological support of AI functionality is the data infrastructure. Strong data structures improve availability and minimise the dynamics of performance (Lee et al., 2020). Poor infrastructures limit the credibility of the system and reduce the perceived usefulness.

According to the model, the positive cognitive evaluations are improved by joint optimisation of the social and technical subsystems. Misalignment, e.g., the introduction of advanced analytics into the low-readiness environments can decrease trust and perceived usefulness. The socio-technical configuration in this way directs the formation of belief that is the core of TAM.

TAM Mediators

The cognitive part of the model is made up of perceived usefulness, perceived ease of use, trust in AI, and intention to use. The perceived usefulness is used to measure how users perceive that AI can improve the performance of the project (Davis, 1989). The usefulness in manufacturing projects can be in the form of accuracy of scheduling, risk forecasting and resource allocation done more wisely. These perceptions are reinforced by socio-technical alignment which indicates reliability and organisational support.

The perceived ease of use is the expected effort to communicate with AI systems. Perceptions of ease are reinforced by easy interfaces, training and smooth integration. Instead, complexity can have an adverse effect on the adoption despite its performance advantages.

Confidence in AI is a lethally necessary expansion of conventional TAM constructs. Artificial intelligence systems work within uncertainty and can produce outputs that do not make transparency in an intuitive manner.

Trust refers to the readiness to depend on the results of algorithms even without confidence (Glikson and Woolley, 2020). It has been found that transparency and reliability are essential in forming trust (Siau and Wang, 2018). The mediation of the translation of the socio-technical alignment into behavioural intention occurs through trust.

Intention to use is the motivational state that is followed by adoption behaviour. In line with TAM and UTAUT (Venkatesh et al., 2003), intention represents cumulative appraisal of usefulness, ease and trust. Intentions determine whether AI recommendations are accepted as part of regular planning and monitoring decisions by team members in project settings or not.

The model includes trust in addition to PU and PEOU, which allows the model to embrace the dynamics of AI-specific acceptance. Trust mediates the system-level design characteristics transparency and reliability on the basis of individual reliance behaviour to scale TAM to human-centred AI ideals.

Outcomes

The conceptual model is on adoption behaviour, defined as the long-term use of AI tool in project work. Adoption goes beyond nominal use to active inclusion into the processes of scheduling, risk assessment and cost forecast. Behavioural reliance refers to the intention-to-practice consistency.

The result is project performance. Performance is a multidimensional concept. Efficiency in the operations means better coordination and resource use, as well as schedule compliance. Predictive analytics can be used to improve the accuracy of planning and minimise delays (Tao et al., 2018). Reduction in errors summarises reduced forecasting errors and better accuracy in decisions, which are consistent with the results that machine learning increases predictive accuracy in a manufacturing setting (Wang et al., 2022).

The relational performance outcomes are expressed in stakeholder satisfaction. Ethical and accountable AI can increase the trust of managers and customers. On the other hand, skepticism may be generated by muddled or insufficiently merged systems regardless of the technical statistics.

The model assumes that there is a mediating variable between cognitive beliefs and performance results, which is adoption. AI capabilities will not be achieved without active reliance. The process of behavioural adoption is therefore the process that converts the perception into performance.

Moderators

The performance linkage is affected by the adoption-contextual moderators. One of the major moderators is project complexity. AI analytics have the potential to benefit complex projects that have interdependent tasks and uncertainty. Complexity can also, however, raise the cognitive load, and this can undermine reliance in case interpretability is inadequate.

A second moderator is the use of formal integration mechanisms. Projects that introduce AI solutions into formal procedures, like the obligatory risk assessment, have higher chances of achieving statistically significant performance changes than those that view AI as a supportive tool.

There are additional moderating factors that are based on the context of an organisation (cultural orientation and digital maturity). These favorable cultures enhance the gains of adoption, and inflexible or risk-averse societies can limit experimentation.

The model also takes into consideration the fact that AI adoption does not equitably lead to performance improvements by introducing these moderators. The contextual contingencies define the size of effects and support the situational approach to the socio-technical acceptance, which is multi-level.

V. PROPOSITION FORMULATION

This section formulates seven propositions, which are theoretically based on the socio-technical model integrated. The propositions express directional relationships between factors of social and technical subsystems, cognitive mediators, adoption behaviour, and project performance outcomes. In line with the multi-level framework of the model, the propositions are ascending towards macro-level socio-technical conditions to micro-level cognitive processes, and finally, to project-level implications.

P1: Social Subsystem → Perceived Usefulness and Perceived Ease of Use

The initial hypothesis concerns the role of the social subsystem variables, namely, the organisational readiness, leadership support, team capability, in the perceived usefulness (PU) and perceived ease of use (PEOU). Under the Technology Acceptance Model, PU, and PEOU are the theoretical beliefs that influence behavioural intention (Davis, 1989). Nevertheless, such beliefs do not come to existence as vacuum, but are contextual cues that can be found in organisational settings.

Organisational preparedness is an indication of group commitment and belief in change implementation (Weiner, 2009). In case of high readiness, the employees tend to perceive the AI initiatives as justified, well-grounded, and strategically consistent. The environments decrease the degree of uncertainty and promote positive sensemaking. The AI systems, in its turn, are more prone to be viewed as helpful, as the introduction of them is being presented as intentional and goal-oriented regarding performance. Similarly, preparedness tends to have investments in training and capability building, which facilitates the ease of use by decreasing cognitive load.

These perceptions are further enhanced by leadership support. Leaders are very important in explaining the justification on use of AI and setting the anticipated usage patterns (Armenakis et al., 1993; Armenakis and Harris, 2009). There is an evident endorsement indicating a strategic significance and less ambiguity as to the value of the system. Leadership framing has a substantial impact on the interpretation of tools in project-based contexts, in which temporary teams are highly dependent on direction and coordination.

Cognitive evaluations also are formed by team capability. The AI systems can frequently generate probabilistic results, which need to be interpreted and incorporated into multifaceted processes of decision making. Highly data literate and team collaborative teams are in a better position to exploit algorithmic recommendations (Jarrahi, 2018). The competence minimises the felt effort and enhances belief in reaping performance advantages, thus enhancing both PU and PEOU.

Proposition 1 (P1): The social subsystem factors (organisational readiness, leadership support and team capability) have a positive impact on perceived usefulness and perceived ease of use of human-centric AI systems in manufacturing projects.

P2: Technical Subsystem → Trust

The second proposal is concerned with the role of the technical subsystem in trust in AI. The AI technologies are opaque, unlike the traditional information systems that usually work based on their algorithms. Reliance is thus a very important factor of trust.

Transparency, especially explainable AI (XAI), boosts the users' level of understanding how predictions or recommendations are made (Gunning et al., 2019; Ribeiro et al., 2016). As long as users are able to understand the logic behind the outputs, the level of uncertainty reduces and confidence becomes stronger. Transparency therefore is a trust-building mechanism.

Trust is also brought about by system compatibility. AI systems that can be implanted easily into the current workflows and tools decrease the friction and signal reliability. Compatibility minimises the feeling of technological discontinuities and confidence in system stability.

System accuracy and reliability are based on the quality of data infrastructure. Strong data architectures enhance the anticipation data and minimise errors (Lee et al., 2020; Tao et al., 2018). Reliability enhances trust as it shows that the performance is consistent in different situations.

Trust in AI has been theorised as readiness to trust the results of fundamental algorithms with uncertainty (Glikson and Woolley, 2020). Empirical evidence indicates that perceived transparency and reliability contribute to trust substantially, whereas the lack of transparency and unpredictability negatively affect it (Siau and Wang, 2018). Trust is something that cannot be adopted in project environments that involve financial and operational risks of the decisions.

Proposition 2 (P2): The characteristics of technical subsystem (AI transparency, system compatibility, and the quality of data infrastructure) determine a positive impact on the level of trust towards human-centric AI systems in manufacturing projects.

P3: Mediation through Perceived Usefulness, Perceived Ease of Use, and Trust
Socio-technical factors precondition the situation but final adoption is attributed to cognitive mediators. TAM assumes that PU and PEOU influence intention to use (Davis, 1989) and UTAUT supports the primacy of intention that is based on belief (Venkatesh et al., 2003).

Trust in AI situations acts in the same manner as PU and PEOU, but as an independent but complementary mediator. Due to the nature of the AI systems as concerns probabilistic reasoning and autonomous learning, users should consider not only the benefits of the performance and efforts but also the reliability and integrity: trust bridges the gap between the system features and behavioural commitment (Glikson and Woolley, 2020).

The formation of beliefs depends on socio-technical alignment, though intention to use is developed with the help of these mediators. Favourite conditions are made through high readiness, supportive leadership, transparency, and the quality of infrastructure, but unless these conditions are converted into positive perceptions of usefulness, ease, and trust, chances of adoption would not be realised. Therefore, PU, PEOU, and trust mediate interrelation of socio-technical factors and intention to use AI.

Proposition 3 (P3): Socio-technical factors have a mediating relationship between intention to use human-centric AI systems and perceived usefulness, perceived ease of use, and trust in AI in manufacturing projects.

P4: Human-Centred Design → Trust and Engagement
In addition to general technical features, human-centred AI (HCAI) principles bring in other design dimensions. Instead of replacement, HCAI gives priority to explainability, accountability, and augmentation (Shneiderman, 2020; Dignum, 2019).
Explainability increases interpretability and decreases cognitive opaque and directly boosts trust. It helps eliminate ethical issues by guaranteeing transparency in terms of system responsibility and the limits of decisions (Floridi et al., 2018). Instead of being competitive, AI is promoted as an ally in augmentation, thereby reducing the chances of competing with a person (Nahavandi, 2019; Romero et al., 2021).
HCAI principles provide users with more chances of engagement and less opposition by maintaining human control and agency. Interaction does not just occur at the level of cognitive belief but also at the level of actively participating in the use of a system. AI systems that are made to supplement expertise will have a high probability of users incorporating the outputs into the decision processes.

Proposition 4 (P4): Concepts of human-centred AI design have a positive effect on trust and user engagement of manufacturing project settings.

P5: Adoption → Project Performance
Adoption behaviour which is the expression of intention into active dependence. The AI-based analytics in manufacturing projects have proven to have an increase in predictive accuracy, schedule optimisation, and resources allocation (Tao et al., 2018; Wang et al., 2022).

This could result in improved operational performance in terms of optimised sequencing, and shortened planning delays. The reduction of errors can be through better forecasting and detection of anomalies. All these improvements are helpful in increasing the performance parameters of the project, such as time, cost, and satisfaction of stakeholders.

Nevertheless, the performance gains can be realised only when AI tools are actively used but not passively accessible. Behavioural reliance is a concept that makes the algorithmic insights integrated into the decision workflows.
Proposition 5 (P5): The adoption behaviour of human centric AI systems positively affects project performance, which is evident through increased efficiency and reduced errors in manufacturing projects.

P6: Moderation by Project Complexity
The level of adoption is affected by the complexity of the project. Very complicated projects are those that have interdependent activities, uncertainty and dynamism in coordinating activities. The AI-driven analytics could be of more value in these situations, as it could handle the informational overload and find the trends that are out of the reach of human intellect.

Complexity can however also increase cognitive loads and therefore trust and interpretability are essential. In simpler projects, the benefits of AI can be incremental; in more complex environments, the benefits of AI can be enormous.

Proposition 6 (P6): Project complexity moderates the relationship between AI adoption and project performance such that the relationship is perceived to be stronger between more complex projects.

P7: Moderation by Formal Integration and Adaptive Project Management
Formal mechanisms of integration enhance the institutionalisation of AI tools. Dependability turns into a routine instead of a discretionary issue when AI generation is introduced into orderly procedures, e.g. when it is mandatory to conduct a risk assessment or a standardised dashboard.

Balancing between hybrid and agile approaches, adaptive project management strategies focus on iterative learning and responsiveness (Gemino et al., 2020). These are environments that are conducive to experiments and evidence-based decision making. Integration magnifies the effect of performance of adoption by making sure that there is the consistency in the application to tasks.

Proposition 7 (P7): The positive relationship between the adoption of AI and the performance of the project is moderated by the formal integration mechanism and adaptive practices in project management.

Together, the seven propositions provide a multi-layered explanation of human-centric AI implementation of manufacturing projects. They are used to mediating socio-technical correspondence, cognitive mediation, human-centred design and contextual moderation in order to offer a holistic theoretical framework to be empirically tested.

VI. THEORETICAL AND PRACTICAL IMPLICATIONS

6.1 Theoretical Contributions

The research contributes to theory, applying both the Socio-Technical Systems (STS) theory and Technology Acceptance Models (TAM/UTAUT) and Human-Centred Artificial Intelligence (HCAI) into a multi-level model of AI acceptance in manufacturing projects. Although both sides have made independent contributions to the knowledge base in their own perspective, their disjointedness has hampered the ability to gain an overall understanding of the integration of AI technologies in complex project environments. The proposed model also focuses on this fragmentation through connecting the macro-level socio-technical conditions with the micro-level cognitive mechanisms and project-level performance outcomes.

To start with, it expands the scope of the STS theory which is usually focused on organisational design and joint optimisation (Trist and Bamforth, 1951; Clegg, 2000). STS has traditionally shown that the performance is determined by the compatibility between social and technical subsystems, but it has not provided a strong explanatory capacity to the formation of beliefs on an individual level. It enhances the model by including TAM constructs as a way of explaining the impact of socio-technical configurations on perceived usefulness and perceived ease of use (Davis, 1989).

Adoption is not directly generated by organisational readiness, leadership support and the quality of infrastructure, but instead, cognitive assessment that converts structural alignment into behavioural intention is affected by them. This expansion expands the theory of STS by elucidating psychological processes with which joint optimisation influences the use of technology.

Second, the framework brings TAM and UTAUT a step further by integrating them into a wider socio-technical framework. TAM has always shown predictive validity in any setting (Davis, 1989), and UTAUT has added explanatory coverage to the other model due to its inclusion of social influence and enabling conditions (Venkatesh et al., 2003). Nevertheless, the models generally consider contextual factors as exogenous factors as opposed to interdependent subsystems. The model avoids this limitation and establishes the conceptualisation of the acceptance as a social and technical construct instead of an individual concept by placing PU and PEOU within a systemic structure based on STS.

Third, the TAM is extended in the study by integrating trust as a major mediator. Probabilistic reasoning, algorithmic opacity, and adaptive learning are some of the differences between AI systems and traditional information systems. The dependency in such situations is not just on the perceived usefulness and ease but also the trust in systems integrity (Glikson and Woolley, 2020). Empirical studies indicate that transparency and explainability lead to trust (Siau and Wang, 2018; Gunning et al., 2019), but neither of these concepts are well embodied in the main acceptance models. The framework includes trust as a formal component alongside PU and PEOU in order to reflect epistemic peculiarities of AI-based decision support. Trust is both a cognitive and an affective judgment, which facilitates the conversion of socio-technical alignment to intention.

Fourth, the incorporation of HCAI principles brings in normative and design-oriented aspect in technology adoption theory. HCAI also focuses on explainability, accountability, and augmentation (Shneiderman, 2020; Dignum, 2019). The model relates ethical design with behavioural outcomes because it has intertwined these principles with trust and engagement. This theoretical addition is especially important in manufacturing projects, whereby AI tools are becoming more important in cost, schedule, and risk decisions. The framework, in turn, promotes a multi-level, interdisciplinary perspective of AI adoption, which is crosscutting between organisational theory, behavioural models, and responsible AI scholarship.

Taken together, the research provides a consistent theoretical framework that can be used to conduct empirical research. It elucidates causal patterns, mediation, and moderating systems and locates individual acceptance in the context of fitting in the system. By so doing, it will be responding directly to calls of integrative frameworks that would explain the digital transformation in project-based organisations.

6.2 Practical Implications

In addition to theoretical progress, the model offers practical advice to practitioners in the field of AI application in the manufacturing projects. The results indicate that effective adoption is not only related to the level of technological sophistication but also to the balanced socio-technical association and design-conformity with the human being.

To project managers, the framework emphasises the need to file organisational preparedness prior to the implementation of AI tools. Preparedness denotes a group trust and willingness to change (Weiner, 2009). The ability of a team, data literacy, and readiness to experiment are some of the factors that managers should consider before implementing AI-based decision support. Positive perceptions and resistance can be reinforced through visible leadership support and orchestrated communication which is in line with change management concepts (Armenakis et al., 1993). Through the creation of augmentation stories instead of replacement, project leaders can create a sense of psychological safety and prompt participation.

Investment in governance mechanisms and training becomes critical to organisations. The users of AI systems have to be people, who are able to understand probabilistic output and incorporate it into their project processes (Jarrahi, 2018). The focus of training programs should be thus made to focus on data literacy, interpretability skills, and collaborative human-AI interaction. The governance systems should also be transparent and accountable, which corresponds to the principles of responsible AI (Floridi et al., 2018). Having explicit rules on how the data will be used, model validation and authority over the decisions will minimise the ambiguity and rebuild trust.

Perceived usefulness and reliability are also promoted with the help of technical investments in the quality of data infrastructure and compatibility between the systems (Lee et al., 2020).

PMOs are strategic to formal integration. Incorporation of the AI output in the processes of standardisation, e.g., risk reviews or scheduling dashboards, will turn discretionary use into a habit.

Iterative learning and AI tools experimentation can be supportable with adaptive or hybrid project management approaches (Gemino et al., 2020). PMOs are able to come up with integration roadmaps where both the socio-technical readiness assessment and phased deployment strategies are synchronised. PMOs guarantee that the investment in the technology leads to the measurement of the project outputs by embedding the evaluation metrics of the AI performance and adoption.

Notably, the model discourages technical implementation strategies. The use of advanced analytics will not ensure a performance increase. Rather, social and technical subsystems are optimised together, and trust and human-centred design are taken into account, which predetermines success. Managers must, therefore, handle AI adoption as an organisational change project and not a software implementation project.

The model indicates that the gains of AI adoption can be more pronounced in the most complicated projects, as long as trust and interpretability should be ensured. Therefore, explainability mechanisms are highly encouraged by practitioners in contexts of high uncertainty. Users can have more confidence and dependency through transparent dashboards and interactive tools of explanation.

In general, the framework has presented a systematic diagnostic and implementation guide. It promotes the idea of organisations evaluating the readiness, investing in developing capabilities, developing transparent systems, and integrating AI into the formal processes. By matching the socio-technical circumstances with cognitive acceptance processes, the practitioners can make AI tools more likely to provide real effects of efficiency, reduction of errors, and satisfaction of stakeholders.

VII. LIMITATIONS AND FUTURE RESEARCH

This study has a number of limitations despite its integrative contributions. To begin with, the model is theoretical and has not been empirically tested. Future studies must also delve into the case of hybrid intelligence arrangements and the effects they have on organisational performance (Jarrahi et al., 2022). Even though the framework is based on the existing theories, such as Socio-Technical Systems (STS) theory (Trist and Bamforth, 1951; Clegg, 2000), the Technology Acceptance Model (Davis, 1989; Venkatesh et al., 2003), and Human-Centred AI principles (Shneiderman, 2020; Dignum, 2019), the relationships are still theoretically obtained. Clear and coherent thinking is given by conceptual integration, but empirical testing is needed to determine the strength of causation, mediation effects and boundary conditions. The predictive ability of the model can not be validated without quantitative validation.

Second, the framework is located specifically in manufacturing project setting. Industry-based comparative research would also be possible to explore the effect of human-centric Industry 5.0 principles on the adoption of AI in other settings (Breque et al., 2021). Even though manufacturing projects offer an appropriate, high-impact setting with the characteristics of technological complexity, cross-functional cooperation, and pressure to undergo digital transformation, the discoveries might not be directly applicable to other industries that follow the project-based model, including the construction industry, healthcare, or software development. Dynamics of adoption could be affected by sector specific factors, regulatory constraints and the level of technology maturity in different ways. Therefore, the theoretical propositions should be interpreted in the context of limitations.

Third, the model focuses on the organisational and cognitive factors of adoption but fails to explicitly include macro-environmental factors like the regulation of the industry, the presence of competition, or the national policy on the digital sector. These larger institutional variables can encourage the preparedness and governance organisations in a manner that is not reflected on the existing framework.

A future study is needed that empirically verifies the proposed relationships. Structural Equation Modeling (SEM) is a suitable analytical method that may be used to test the multi-level mediation framework, especially indirect effects of socio-technical factors via perceived usefulness, perceived ease of use, and trust (Venkatesh et al., 2003). SEM would allow parallel measurement validity and structural evaluations which would give rigorous assessment of model fit.

Quasi-experimental designs might also better support the causal argument by comparing AI-integrated projects to those with more AI.

As an illustration, the results of the projects where human-oriented AI was implemented might be compared to the outcomes of the projects which use the conventional decision-support, which would allow evaluating the moderating impact of the project complexity and formal integration mechanisms.

It is also suggested that mixed-method approaches are also desirable. Qualitative case studies would give out the contextual complexity and investigate how socio-technical alignment takes place in practice in line with STS traditions of focusing on a system level analysis (Clegg, 2000). Cognitive constructs that may be measured to include trust and perceived usefulness at scale are complemented by survey-based research. With the evidence provided in a case and the quantitative testing, the future studies will be able to refine the model, determine the contingency and improve the generalisation across the industries and technological levels of maturity.

VIII. CONCLUSION

The purpose of this paper was to constitute a comprehensive conceptual framework of adoption of human-centred artificial intelligence (AI) in manufacturing project contexts. The research based on a multi-level model of the relationship between socio-technical alignment, cognitive intermediates, adoption behaviour, and project performance outcomes was suggested to respond to fragmentation across the Socio-Technical Systems theory (Trist and Bamforth, 1951), Technology Acceptance Models (Davis, 1989; Venkatesh et al., 2003), and the Human-Centred AI scholarship (Shneiderman, 2020).

The model pursues a sequential line of reasoning where social and technical subsystem variables determine perceived usefulness, perceived ease of use and trust in AI. These cognitive mediators are the ones that have an impact on intention and consequent adoption behaviour and as a consequence these mediate project efficiency, error reduction and stakeholder satisfaction. The framework involves macro-level structural alignment and micro-level belief formation through the introduction of trust as a fundamental mechanism and the construction of acceptance constructs into the framework of systemic organisational conditions. Contextual contingencies added further by the moderating effects of project complexity and formal integration clarify the outcomes of performance.

The theoretical value is the combination of structural, behavioural, and design-oriented perspective into a logical explanation of AI adoption in project-based organisations. In practicum, the model emphasises the point that technological sophistication is not a guarantee in performance improvement. Rather, it has to be optimised in collaboration with social and technical subsystems and followed by the principles of the human-centred design with its focus on transparency, accountability, and augmentation.

With the shift of manufacturing towards more and more intelligent and data-driven manufacturing, human-oriented AI is becoming not only a technical breakthrough but also an organisational necessity. It will be necessary to align AI potentials with human skills and trust-based mechanisms to achieve sustainable project performance increases.

REFERENCES

[1] Lee, J., Bagheri, B., & Kao, H. A. (2020). A cyber–physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters, 3*, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001

[2] Kang, H. S., Lee, J. Y., Choi, S., Kim, H., Park, J. H., Son, J. Y., … & Do Noh, S. (2016). Smart manufacturing: Past research, present findings, and future directions. *International Journal of Precision Engineering and Manufacturing-Green Technology, 3*(1), 111–128. https://doi.org/10.1007/s40684-016-0015-5

[3] Nahavandi, S. (2019). Industry 5.0 — A human-centric solution. *Sustainability, 11*(16), 4371. https://doi.org/10.3390/su11164371

[4] Romero, D., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fast-Berglund, Å., & Gorecky, D. (2021). Towards an operator 5.0 typology: A human-centric perspective on the fifth industrial revolution. *Computers & Industrial Engineering, 158*, 107379. https://doi.org/10.1016/j.cie.2021.107379

[5] Zhou, K., Liu, T., & Zhou, L. (2015). Industry 4.0: Towards future industrial opportunities and challenges. In *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)* (pp. 2147–2152). IEEE. https://doi.org/10.1109/FSKD.2015.7382284

[6] Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems, 48*, 157–169. https://doi.org/10.1016/j.jmsy.2018.01.006

[7] Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems, 48*, 157–169. https://doi.org/10.1016/j.jmsy.2018.01.006

[8] Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation, 122*, 102623. https://doi.org/10.1016/j.technovation.2022.102623

[9] Shneiderman, B. (2020). Human-Centered Artificial Intelligence: Three Fresh Ideas. *AIS Transactions on Human-Computer Interaction, 12*(3), 109-124. https://doi.org/10.17705/1thci.00131

[10] Dignum, V. (2019). *Responsible artificial intelligence: How to develop and use AI in a responsible way*. Springer. https://doi.org/10.1007/978-3-030-30371-6

[11] Jarrahi, M. H., Lutz, C., & Newlands, G. (2022). Artificial intelligence, human intelligence and hybrid intelligence based on mutual augmentation. *Big Data & Society, 9*(2), 1–6. https://doi.org/10.1177/20539517221142824

[12] UNESCO. (2021). *Recommendation on the ethics of artificial intelligence*. https://unesdoc.unesco.org/ark:/48223/pf0000381137

[13] Tóth, A., Nagy, L., Kennedy, R., Bohuš, B., Abonyi, J., & Ruppert, T. (2023). The human-centric Industry 5.0 collaboration architecture. *MethodsX, 11*, 102260. https://doi.org/10.1016/j.mex.2023.102260

[14] Turner, R., & Miterev, M. (2019). The Organizational Design of the Project-Based Organization. *Project Management Journal*, *50*(4), 487–498. https://doi.org/10.1177/8756972819859746

[15] Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

[16] Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

[17] Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

[18] Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *International Journal of Intelligent Systems, 33*(4), 436–452. https://doi.org/10.1002/int.21904

[19] Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G. Z. (2019). XAI – Explainable artificial intelligence. *Science Robotics, 4*(37), eaay7120. https://doi.org/10.1126/scirobotics.aay7120

[20] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1135–1144. https://doi.org/10.1145/2939672.2939778

[21] Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors, 39*(2), 230–253. https://doi.org/10.1518/001872097778543886

[22] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

[23] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003, September). User Acceptance of Information Technology: Toward a Unified View. ResearchGate; University of Minnesota, Management Information Systems Research Center. https://www.researchgate.net/publication/220259897_User_Acceptance_of_Information_Technology_Toward_a_Unified_View

[24] Clegg, C. W. (2000). Sociotechnical principles for system design. *Applied Ergonomics, 31*(5), 463–477. https://doi.org/10.1016/S0003-6870(00)00009-0

[25] Weiner, B. J. (2009). A theory of organizational readiness for change. *Implementation Science, 4*(1), 67. https://doi.org/10.1186/1748-5908-4-67

[26] Armenakis, A. A., Harris, S. G., & Mossholder, K. W. (1993). Creating Readiness for Organizational Change. *Human Relations*, *46*(6), 681–703. https://doi.org/10.1177/001872679304600601

[27] Armenakis, A. A., & Harris, S. G. (2009). Reflections: Our journey in organizational change research and practice. *Journal of Change Management, 9*(2), 127–142. https://doi.org/10.1080/14697010902879079

[28] Mudgal, P. (2025). A data-centric framework for implementing artificial intelligence in smart manufacturing. *Electronics, 14*(16), 3304. https://doi.org/10.3390/electronics14163304

[29] Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). *A model for types and levels of human interaction with automation. IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans, 30*(3), 286–297. https://doi.org/10.1109/3468.844354

[30] Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

[31] Rai, A. (2020). Explainable AI: from Black Box to Glass Box. *Journal of the Academy of Marketing Science*, *48*(1), 137–141. https://doi.org/10.1007/s11747-019-00710-5

[32] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., … & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689-707. https://doi.org/10.1007/s11023-018-9482-5

[33] Jobin, A., Ienca, M., & Vayena, E. (2019). *The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

[34] Hagendorff, T. (2021). Linking human and machine behavior: A new approach to evaluate training data quality for beneficial machine learning. *Minds and Machines, 31*(4), 563–593. https://doi.org/10.1007/s11023-021-09573-8

[35] Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *International Journal of Intelligent Systems, 33*(4), 436–452. https://doi.org/10.1002/int.21904

[36] Breque, M., De Nul, L., & Petridis, A. (2021). *Industry 5.0: Towards a sustainable, human-centric and resilient European industry*. European Commission, Directorate-General for Research and Innovation. https://op.europa.eu/en/publication-detail/-/publication/468a892a-5097-11ec-91ac-01aa75ed71a1

[37] Longo, F., Nicoletti, L., & Padovano, A. (2017). *Smart operators in Industry 4.0: A human-centered approach to enhance operators' capabilities and competencies within the smart factory context. Computers & Industrial Engineering, 113*, 144–159. https://doi.org/10.1016/j.cie.2017.09.016

[38] Mudgal, P. (2025). A data-centric framework for implementing artificial intelligence in smart manufacturing. *Electronics, 14*(16), 3304. https://doi.org/10.3390/electronics14163304

[39] Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors, 39*(2), 230–253. https://doi.org/10.1518/001872097778543886

[40] Pan, Y., Ahmi, A., & Raja Mohd Ali, R. H. (2024). A human-centric approach for smart manufacturing adoption: An empirical study. *Journal of Distribution Science, 22*(1), 37–46. https://doi.org/10.15722/jds.22.01.202401.37

[41] Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. *Human Relations, 4*(1), 3–38. https://doi.org/10.1177/001872675100400101

[42] Passalacqua, M., Pellerin, R., Magnani, F., Doyon-Poulin, P., Del-Aguila, L., & Boasen, J. (2024). Human-centred AI in Industry 5.0: A systematic review. *International Journal of Production Research, 63*(7), 2638–2669. https://doi.org/10.1080/00207543.2024.2406021

[43] Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

[44] Gemino, A., Horner Reich, B., & Serrador, P. M. (2020). Agile, Traditional, and Hybrid Approaches to Project Success: Is Hybrid a Poor Second Choice? *Project Management Journal*, *52*(2), 875697282097308. sagepub.