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Breaking the chain of knowledge transfer: AI shadows implicit, explicit, and tacit exchange

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Abstract

This study is a meta-analysis review investigating the notion of adopting applied Artificial Intelligence (AI) systems into" knowledged" roles and practices, where the traditional Knowledge Transfer (KT) from the expert human to successor human is disrupted, thereby the transference of knowledge ceases. Through the transformation of human practice to machine function, the notion of knowledge transference between the layers of KT, exposes the tacit, implicit and explicit exchange with segmentation of a blurred line between the human-machine and machine-human, where this shadows discernment of human knowledge compatibility with generative AI advancements. The belief of advanced generative AI can create a knowledge-gap between human and machine where the impact of human understanding and expertise diminishes and the human capacity of understanding the knowledge-object will be un-transferable to future human successors in their domain. From this perspective it becomes plausible that this can impede advancement of specialized knowledge transfer and method of sole human innovative development in that field. In conclusion, this research hinges on the perspective that specific human knowledge-objects need preservation and capability of direct KT propagation to human successors. This necessitates complete transferable knowledge which carries the seed of human based future innovations. .

Keywords: knowledge transfer, implicit knowledge, explicit knowledge, tacit knowledge, artificial intelligence, information systems

Introduction

This study examines the breakdown of human transferred knowledge that has pushed us forward to the Modern Era Fourth Industrial Revolution, where this new changing paradigm to human-machine and machine-machine breaks the chain of current knowledge transfer process (Davis, 2016). As Artificial Intelligence (AI) systems integrate throughout the landscape, its role, function, and dominion are becoming an integral advancement in human progression (Anyoha, R., 2020).

The use of Artificial Intelligence in building organizational success is the hinge point, where the potential of governing human function is in perspective and through a maturation process, where it will reach its full potential as an AI system (Stegh, August 2024). As the thirst for AI systems drives future integration, there is a strong belief that AI will be positioned to innovate organizations to become productive dominating organizations, the beliefs are the systems will be learning, developing, creating standards, and moving forward, eventually to the forefront (Stegh, September 2024). Furthermore, in this advancement of technology progressing mankind forward, there will be trade-off with the traditional processes of the past to the new machine methods. Influences of technology from Roger's (2005) works help one to understand the embracing of new technologies and changing forces on obsolete methods. Therefore, one may reason the obsolescence of traditional methods is essential in progression as a civilization into a greater position; however, theorists also considered the consequences of technology change and impact on society.

Problem

Given the notion that Artificial Intelligence is being implemented in numerous areas in this stage of technological advancement, the perceived wedging-off of the human role in the exchange of tacit, implicit, and explicit knowledge raises the open concern of impact of future progress from a singular human perspective. Furthermore, to substantiate this impression, with AI ease-of-use lessening human focus on minutiae, providing immediate results, and its ability to process through immense data points; AI further bridges the machine-human relationship. This productive, coupled, system promotes even further use, aligning adoption as tied to the even to more ease with machine-machine, thus considering the Technology Acceptance Model (TAM) acceptance theory (Davis,1989). The Task Technology Fit (TTF) model suggests that human performance correlates well to information technology performing function, thereby considering the great benefits of AI in productivity; however, the weakness hinges on the lack of human need in that task (Goodhue & Thompson, 1995). In addition, the necessity of Knowledge Transfer (KT) encompassing tasks and processes once shepherded through human interaction, will no longer be medium to carry this knowledge. This rationale brings forth two questions in examining the consequences of extinguishing inherent knowledge over time and no longer having a long-term capability of bringing forward this knowledge object (KO) within the innovative human construct.

Q1: *Are humans at risk of losing the body of knowledge through the elimination of person-to-person knowledge transfer?*
Q2: *Are humans at risk of losing tacit, implicit, and explicit understanding of knowledge-objects in their domain of expertise?*

Purpose

Given the wide brush of KT, it is used across extensive interchanges such as in business, engineering, healthcare, science, manufacturing, and technology. In addition, there are many methods and processes that carry the delivery of knowledge and information from its source to a recipient. As well, there is a common thread woven in each of the domains with the subject matter expert (SME), with the inherent subject matter knowledge (SMK) that converges between the tacit, implicit, and explicit transference of knowledge to a successor. The process of Knowledge Transfer is a continuous mechanism, and each category of transference attains methods beyond explicit documentation. For example, tacit knowledge is hidden and resides within 'self-cognitive" boundary such as faith and values, as Wu, Kao, and Shih leans to the works of Nonaka and Takeuchi and D'Eredita and Barreto (Wu, Kao, & Shih, 2010).

Considering the complexities of KT, as innovation is at the cusp of powerful systems with access to unfathomable depth of data and with capacity to process and retain everything, it is natural for humans to harness this extraordinary technology, thus using it to further build civilization and progress forward in life quests. In the adoption of this innovative step forward embedded in Artificial Intelligence, the importance of this research is to examine the consequential impacts that may develop with the integration of new systems and processes, thereby to address the potential problems as society fosters the transition, select human knowledge is not lost, as well as skills and capabilities that are critical to future advancements. Furthermore, leaning into the machine has improved lives in significant measures such as airplanes and automobiles, thus rational tools that empowered us. Nevertheless, AI has the aptitude of learning, decision-making, performing, and becoming self-cognitive, regenerative, generative, and self-advancing. As people explore the perceived knowledge gap and transition between human and perceived concept of future AI implementations, how will society attain KT compatible with human development forward.

Background - Literature Review

Evolving to this next passageway of technology innovation and development for this research, understanding a two-fold approach is necessary converging the cross-points of traditional Knowledge Transfer through human-to-human measures cross paring with both human-to-machine integration and machine-to-machine knowledge advancement. Discussed will be the attributes of KT which encompasses tacit knowledge, implicit and explicit knowledge. These knowledge attributes are fundamental to the advancement of knowledge objects, thus passing skills and knowledge as building blocks to successors for human progression of knowledge (Polanyi, 1962). As Artificial Intelligence systems advance, thereby interconnecting databases, computing platforms, networks, human-coexisting devices to perform the works of humans in both partnered human-machine and machine-machine integrative relationships. AI driven systems are elevating into humanoid companion bots, also known as malebots and gynoids (sfdictionary.com). The AI technology, at this point in life has progressed and is being propagated into all segments. Behind this surge in adoption, there is a magnitude force of business ventures, evidenced by the U.S. Government's $4 billion investment in support of the agreement between SoftBank Group Corp., OpenAI Inc., and Oracle (Vlastelica, 2025) and the recent partnership agreement between the United States and United Arab Emirates for AI hardware (Slattery, *et al.*, 2025).

Knowledge Transfer

Previous research reflects a wide range of topics concerned with knowledge transference. Many of the earlier studies raise the same major concern; explicit knowledge is easily transferred person-to-person, through established KT media, or via existing or emerging technologies. However, it is the transmission of tacit knowledge that raises the most concern throughout the literature.

The research of Maursetha and Svensson (2020) postulated that one of the greatest examples of passing along tacit knowledge is the patent process; in particular when items are commercialized. No one is more knowledgeable of a product than its inventor. The patent application represents the transference of explicit knowledge, as the item must be described in detail. However, it is the tacit knowledge of the product, known only to the inventor, that allows the product to be altered, enhanced, or adjusted in such a way that mass production can occur while not losing the original concept the item was designed.

Nonaka's SECI Model (1994), the standard in KT research, depicts four conversion modes: Socialization, Externalization, Combination, Internalization generated by the process of switching from one type of knowledge to another (Farnese, *et al.*, 2019). Fenstermacher (2005) proposed that tacit knowledge is still knowledge that can be passed along to others, man or machine. Expert knowledge on a subject is often mislabeled as tacit knowledge, leading to belief that it is knowledge that cannot be handed down. Osterloh and Frey (2000) postulated that an organization's structure can be more conducive to KT than others. Businesses with an organizational culture promoting the sharing of knowledge with coworkers created a competitive advantage over organizations where KT was forced onto employers. Collins and Hitt (2006) summarized the key factor in the transfer of tacit knowledge, stating "Tacit knowledge transfer requires greater trust between partners than does explicit knowledge transfer" (p. 148). They go on to cite previous research showing efforts combining similar industries for one goal often leading to unsuccessful partnerships on certain projects. Conversely, work done across multiple people in the same industry leads to positive knowledge transfer results. In this example, the motion picture industry (p. 151).

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Human interaction is still the best method of knowledge transfer. In business, that transfer can be stymied by emotion. Employees can keep information to themselves as a measure of job security, knowing information or processes that no one else in the company is trained on. (Stachová, *et al.* 2020) This concept crosses multiple vocations, from co-workers in an office setting to chefs in Michelin rated restaurants (Di Stefano, *et al.,* 2014). Avdimiotis (2019) built off both Fenstermacher and Nonaka, postulating that the human factor applies knowledge in a way that a computer (or AI) simply cannot calculate, due to personal experience and anticipation of the future. *Basically, AI cannot get a "gut feeling" on a given subject.* (Our emphasis).

Regardless of the countless studies showing personal transfer of knowledge is best, Johannessen, Olaisen, & Olsen (2001) note that companies continue to heavily invest in technology to achieve their KT goals:

> "Although empirical evidence indicates a lack of support for the positive economic impact, we have seen that companies increasingly invest in IT. As this technology is limited to the transfer of explicit (codifiable) knowledge, our concern is that this may relegate tacit knowledge to the background, in spite of this knowledge being emphasized by the literature as an important strategic resource for most companies. Hence, leading to the mismanagement of knowledge." (p. 4)

They go on to remark "Tacit knowledge is as real as explicit knowledge, but the processes to acquire this kind of knowledge relies on awareness of details which cannot be specified or tested in any known scientific way." (p. 7) Nowhere is the process of Knowledge Transfer more obvious, across all industries and professions, than during the onboarding and training of new employees. The onboarding process for a single employee is one of the most expensive, in terms of time, knowledge, and money.

> "It's impossible to concretely state the average onboarding cost for a new hire, but a study from SHRM estimated the average cost of employee onboarding is around $4,100 per new hire. This number will not match individual, personalized use cases, as costs will range based on industry and role, but it's good to have a benchmark that sets the direction for your own estimates." (Olmstead, 2025. Para. 5)

Countless studies have investigated what makes for a successful onboarding program. Are employers willing to take a $4,100 gamble (or more) per new hire, trusting the process to be done adequately by an AI generator? Second, can AI account for a process that can take anywhere from six to 24 months, depending on the complexity of the position and the social structure within the organization? And finally, can AI replicate the socialization aspect of the hiring process? Moreover, can a computer program teach norms, behaviors, and common practices? (Haave, Vold, & Kaloudis, 2020) In the healthcare field, a metastudy of 79 *Healthcare* Knowledge Management articles determined there are six key components to the knowledge transfer and exchange: Message, Stakeholders and Process, Inner Context, Social, Cultural and Economic Context and Evaluation. (Prihodova, *et al*., 2019) Roux, *et al* (2006) noted there is a 'push' and 'pull' relationship between scientists and managers transfer data to one another, with a learned stereotype that scientists push their knowledge down, while managers pull the data they need for a given task.

> "True knowledge transfer will end with adoption, where the adopter has both the absorptive capacity (understanding), as well as the emotional and financial commitments to allow sustained use of the acquired knowledge. Knowledge transfer efforts that do not result in adoption are failures. Although the pushing and pulling strategies described above are increasingly practiced and achieve some success, we still see too many failed transfer attempts." (p. 6)

This Push/Pull relationship does not account for the tacit aspect of knowledge transfer. Explicit knowledge is what is transferred, with a great feedback loop required to make up the difference.

> "Operational management represents a combined explicit–tacit knowledge domain dealing with infrastructure and organizational capability. Explicit knowledge comes in the form of guidelines and manuals, and tacit knowledge is based on experiential learning and verbal sharing of good practice as well as failures." (p. 8)

As the literature shows, Knowledge Transfer is best performed at the human level, person-to-person, especially with tacit knowledge; although implicit knowledge is also difficult to capture and transfer to a successor. Human beings simply cannot download memories and experiences into a computer mainframe and consider their knowledge transferred, no matter how many comic books and Hollywood movies say otherwise. There is no compatible integration for knowledge function between the human and computing ecosystems. Perhaps future innovations with nano-technology and computing-interfaces connecting to the brain will lead us further to these advancements (Neuralink, n.d).

Methodology

The methodology of this study is a meta-analysis using various models and theories to review articles and previous research already performed on these topics, combining the existing research into a cohesive discussion on the present and future of Knowledge Transfer, if AI affects the process of KT, and how that impact may traverse into unforeseen outcomes. This methodological research approach was through comparison of scholarly literature, "current culture", and research models including the Technology Acceptance Model (TAM), the Task Technology Fit (TTF) model, and Nonaka's SECI model.

Built upon the theories and processes, the models and literature examined were the basis of the constructed models used in the discussion of this study, where concepts were extrapolated in discussion with rationale in open perspective to assess and formulate insight and forward understanding of this work. The focus on this research considered the following research questions to consider in this investigation.

> **Q1**: *Are humans at risk of losing the body of knowledge through the elimination of person-to-person knowledge transfer?*
> **Q2**: *Are humans at risk of losing tacit, implicit, and explicit understanding of knowledge-objects in their domain of expertise?*

Table 1 identifies the four core themes in this study and references, thus derived in the meta-research approach where the themes hinged on supporting the adoption of technology with the prolific alignment of AI, the mechanisms in knowledge management, and knowledge transference.

Table 1. Maps core themes of the research to the bibliography references substantiating the study directive.

Themes	Reference
Adoption of Technology	Anyoha (2020) Davis, F. (1989) Davis, N. (2016) Goodhue, D. & Thompson, R. (1995) Rogers, E. M. (2005) Schaller, R. R. (1997)

Themes	Reference
Applying Artificial Intelligence	Eaton, (2016) Fenstermacher, K. D. (2005) Kosmyna, N., Hauptmann, E., Yuan, Y. T., Situ, J., Liao, X.-H., Beresnitzky, A. V., Braunstein, I., & Maes, P. (2025) Meskó, B., Hetényi, G. & Győrffy, Z. (2018) Slattery, G., Mills, A., Maccioni, F., & Saba, Y. (2025) Spiekermann, S. (2022) Stegh, C. (2024) Vlastelica, R. (2025)
Knowledge Management	Farnese, M. L., Barbieri, B., Chirumbolo, A., & Patriotta, G. (2019) Fleck (1996) Maurseth, P. B., & Svensson, R. (2020) Nonaka, I. & Takeuchi, H., (1995) Nonaka, I. (1994) Polanyi, M. (1962)
Knowledge Transference	Avdimiotis (2019) Collins, J. D., & Hitt, M. A. (2006) Di Stefano, G., King, A. A., & Verona, G. (2013) Haave, H., Vold, T., & Kaloudis, A. (2020) Johannessen, J.A., Olaisen, J., & Olsen, B. (2001) Olmstead, L. (2025) Osterloh, M., & Frey, B. S. (2000) Prihodova L, Guerin S, Tunney C, Kernohan WG. (2019) Roux, D. J., Rogers, K. H., Biggs, H. C., Ashton, P. J., & Sergeant, A. (2006) Stachová, K., Stacho, Z., Cagáňová, D., & Stareček, A. (2020) Wu, C.H., Kao, S.C., & Shih, L.H. (2010)

The essence of the research questions are to be the lens to examine the adoption of AI innovation as it is accepted through the landscape, where there is a balance of preservation and advancement to establish a grounded framework in moving forward with assurance of the body-of-knowledge. Respectful to the aforementioned questions, the process and methodology of this work is to substantiate the notion that specific human skills are being diminished, where their inner knowledge and the transfer of that knowledge or the ability to forward that knowledge to future successors is without harm. Thus, the impact of this work through this process of previous scholarly works from others is to affirm their theories hold true and allow us to continue to bridge forward and adopt new scientific and technological ways of life with a grounded foundation.

Discussion

The discussion examines the two main themes: human-to-human and machine-to-machine knowledge transfer, where the cross-comparison of the two platforms and the progression forward may have consequential impact to human control of buildable knowledge units that were fundamental to technological advancements. The Artificial Intelligence construct is a convergence of decades of evolutionary technology development, and certainly brings to the forefront of innovation extended capabilities, thereby advancing the human ability to process more and improve human existence. As further adoption of AI being a disruptor technology, exploration of unintended consequences is necessary to help the forward progression of these systems and continue to build the human role in advancement. The area of KT bears investigation, where the role of the computing systems step into the human process, gating SME controls in knowledge areas. The deeper focus of the study specifically looks at the notion of these two questions “Q1: Are humans at risk of losing the body of knowledge through the elimination of person-to-person knowledge transfer?”

and "Q2: Are humans at risk of losing tacit, implicit, and explicit understanding of knowledge-objects in their domain of expertise?".

A recent study released by MIT (Kosmyna, *et al.*, 2025) supports the answer to both research questions as a plausible yes. Subjects in their experiment showed a cognitive decline with prolonged use and exposure to an AI program, ChatGPT specifically, where this parallels the notion of associated KT practices.

Etched in the transferable exchange of human expertise, "knowledge DNA" is encoded with tacit, implicit, and explicit understanding, that was brought forward in that approach. As this research hinged on the potential consequential lens of losing the transference of knowledge, where the current human role in this partnership with AI no longer has hold of the tacit, implicit, and explicit measures of KT once the relationship between human and machine is in full cycle. To demonstrate the relationship of AI impact on cognitive and applied knowledge transference, Table 2 illustrates the relationship between knowledge types and the characteristics of transferred knowledge.

Table 2. Relationship between tacit, explicit, and implicit knowledge in a transference relationship.

Knowledge Type	Knowledge Transference Loss
Tacit	Non-transferable knowledge from humans, thus the most difficult to capture and transfer forward as well as from machine to human.
Explicit	Ease of transfer, fact based, and can be internal or external to an organization. Current transference method of human to machine and from machine to human.
Implicit	Difficult to capture and transfer to a successor, where the knowledge owner has the details, and may attribute gaps in knowledge transference.

Further bridging the transference association, Figure 1 demonstrates this notion where the dichotomic relationship eventually removes the human from the process, bearing no further need for the creature to perform, understand, or promote to the successor. Laser focus on the successor becomes machine-to-machine migration or upgrade, whereas solely human-to-human or human-machine-human is no longer compatible with the knowledge position in technology at that time. Noteworthy to mention is the inverse relationship, where the human knowledge of process will decrease and the learned AI knowledge increases, thus eventually eliminating the subject matter expert in the transference process.

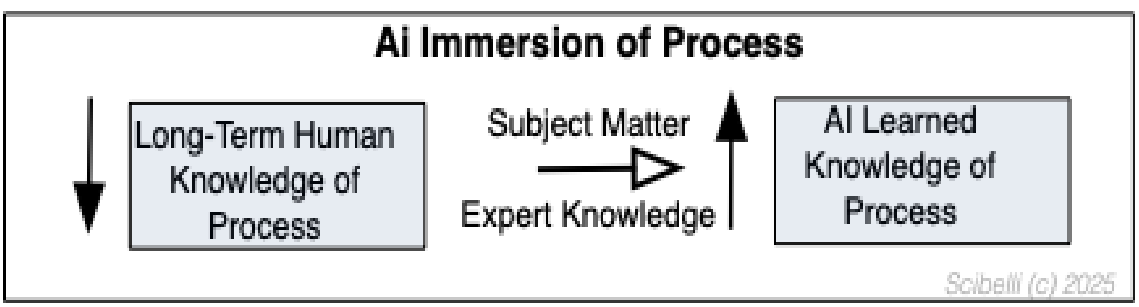

Figure 1. Demonstrates the dichotomic relationship of direct knowledge and understanding of tasks and function from human, passed to machine, where the human subject temporarily assists, then no longer performs that operation.

Traditional knowledge transfer between humans was the method of how civilizations were built throughout history. The human shaping and understanding of everything were carried through expression of tacit, or self-unknown knowledge; implicit, bearing the individually-known knowledge, and explicit, the shared body-of-knowledge. This encapsulated construct of knowledge transference is the foundation, hem-

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stitched over time, through human ingenuity with the strands of information connecting each advancement node through time. As illustrated in Figure 2, the relationship between the human subject sharing forward the understanding and knowledge of the knowledge-object to another human, thereby allowing for the transference of this data, information, or practice. Therefore, this is the traditional method of knowledge transfer. The components of this human comprehension exchange create the rails for the track, forward bound with the unmeasurable strength of tacit knowledge with nuisances embedded and hidden, thereby unknown or undocumented. The influence of human elements (personal experience, beliefs, etc.) run deep in tacit knowledge, as "tacit knowledge does not involve the generation and acquisition of tangible products and processes, or the more formal element of intangible knowledge flows associated with specific research, technical, or training programs" (Fleck 1996, p. 119).

Nonaka (1994) suggests the most arduous articulation within knowledge transference is implicit knowledge gained through shared experiences. The implicit known elements of the knowledge-object that is specific to the human propagator that is typically captured through observation. Where this knowledge is less formalized, it is essential in the construct of the knowledge-object. Explicit knowledge represented in the model is typically shared knowledge and is accessible through documented artifacts both internal proprietary or external to the populous. (Nonaka, 1994)

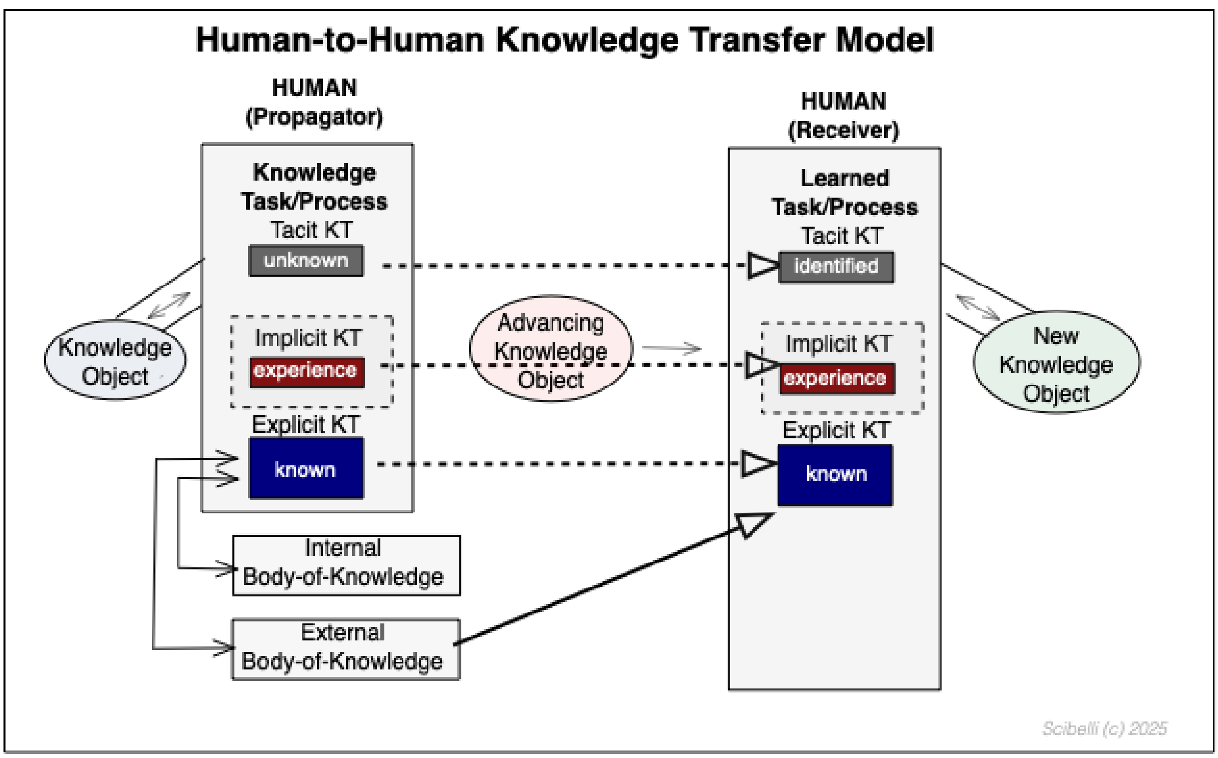

Figure 2. Illustrates the KT between human-to-human where tacit, implicit, and explicit is transferred to a successor.

As humans transfer their knowledge to the transcending machine, the role of a Subject Matter Expert (SME) is to train the AI system to perform the task, with the intent for the machine to out-perform the human and have extensive capabilities to process beyond the original human function. This has occurred in cases of AI machine adoption, the healthcare field in particular (Meskó, Hetényi, & Győrffy, 2018). Figure 3 describes this process where the human SME exchanges knowledge with the machine, thereby training the system with the necessary knowledge to assure machine competence in function. Certainly, the outcome of having systems perform sometimes tedious tasks or procedures requiring repetitive precession beyond human capabilities greatly benefits civilization existence in many ways. (Eaton, 2016)

However, there is also risk of degradation in human competencies in areas where the SME would develop and train their successor in that domain, but the machine is the next link in the chain, and the human successor is no longer necessary in that role. This suggests two areas of concern in that model. First, the human review block in the illustration will eventually fulfill its role as supervisor for AI, thus the system has gained competency, adopting the tacit and implicit knowledge of the trainer. In addition, the machine has access to the explicit, and one would suggest even a larger body-of-knowledge than the trainer. The objective has been completed by the subject matter expert and AI learner. There is no need for a successor to receive the tacit, implicit, or explicit understanding of the knowledge-object. In general, one could believe that the knowledge-object is no longer necessary for humans to understand, thereby coming to the second concern. How does one know what knowledge-object is not needed for the advancement of civilization? As a historical example, the Roman Empire lost the recipe for cement, but humans figured out a replacement many years later in 1824, and a better product, but what happened in between (International Cement Review, 2024)? One would think the landscape would be established with even more ancient bridges, buildings, and travel paths. As well, how many civilizations would still be in existence with their fortresses, thus the world stage may be completely different than what is reflected in the modern world. It is hard to speculate the impact of what could have been; however noteworthy to mention, losing the knowledge-object yields unforeseen and unknown outcomes.

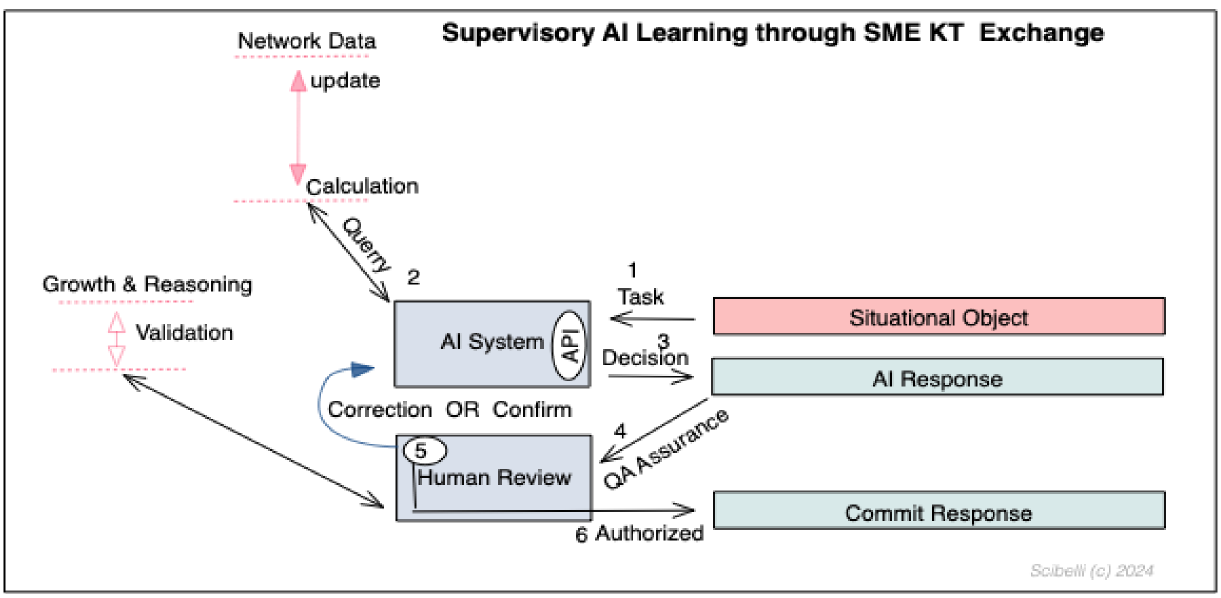

Figure 3. Demonstrates KT from the human to the machine during the SME supervisory phase of AI machine implementation of performing operational tasks.

Now consider the scenario in knowledge transfer where the human is on the periphery of the machine, thereby not in the KT channel of knowledge-object or in the migration, update, or upgrade of the system processing as shown in Figure 4. In this phase of AI technology diffusion, the systems are operating with competence and accuracy as advanced through their mechanisms and evolution process that were once aided by the predecessor human SMEs in the field. Consideration of random human output assessments would be plausible at first transition; however, the assessment measures could potentially be embraced through AI machine "learned" systems and automated methods to serve as QA. As this notion approaches fruition, the human co-pilot bearing the regressive human relationship with the machine is air-gapped from the machine as it implements regenerative advancements through measures such as genetic-programming, thus self-developing code. The machine creates the internal tacit and implicit knowledge at this point, thereby the machine advances beyond the knowledge transference ability to share back the knowledge-object complexities with humans. The knowledge is now in machine codified terms and structure, thus requiring intricate measures for humans to ever extract and adapt from. Considering the disconnect between machine and human at that point, created is a split-brain phenomenon, where humans could no longer communicate with the machine in the terms of the knowledge space within the new machine knowledge-object. The link in the chain that connects once human-to-human or human-to-machine knowledge transfer is broken. The human will no longer be able to sync up with the knowledge path of the machine. Furthermore, the algorithmic changes have been self-made by the machine with ease, and are updated and propagated across other platforms. This depicts a knowledge-object that is easily transferred and implemented instantaneously with other machines performing that task. These adjustments made by the machine are lost in the human contributor and will not be carried forward in the human knowledge of understanding knowledge-objects in its succession.

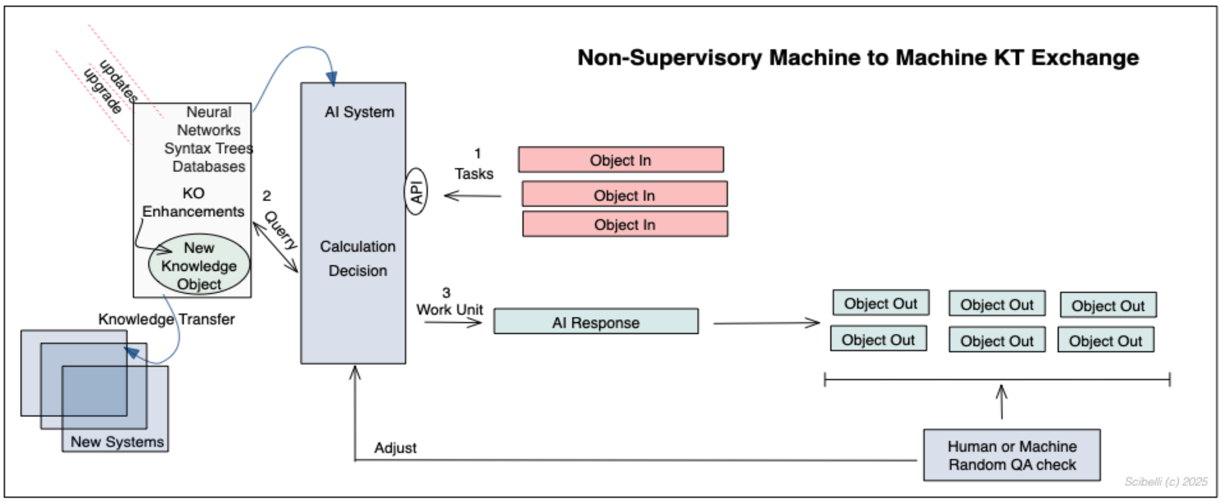

Figure 4. Standalone AI machine sustainability with periphery human or machine performing random QA assessment, where KT of KO is transferred through inner-machine communications

As humans no longer perform specialized tasks, they will eventually lose the inherent knowledge fundamentally innate to the knowledge-object as required. An example of this notion potentially exemplifies the evident acts such as where brain cells will atrophy when no longer used (Utah State University, 2013), similar to how muscles will weaken when they are no longer used in the human body (Cleveland Clinic, 2025). As muscle memory is not used in doing tasks, there will be diminished function. If one is not learning or solving problems, there is a cognitive decline. Hinging on the main fulcrum, if human understanding of a knowledge-object is diminished and the elements of knowledge are not attained or communicated to its successor, then that craft will not be passed to the next descendant or keeper of the knowledge. The benefit and uniqueness of AI is that it is a means of offloading and improving upon human works, as tools that are built and cherished. Eventually people will adapt to the tool, thereby the tools will shape lives as they are integral to our existence as inferred through McLuhan works of Father Culkin (McLuhan Galaxy, 2023). As tools have become better throughout time, Artificial Intelligence has the potential of being one of the greatest innovations, thus it has been built upon decades of technology invention converging to at the apex of many parallel paths forward (Schaller, 1997). In addition, as humans continue to build better, the processing and capabilities of technology will continue onward with no end.

During that progression how much of the inner workings of the machine function will be tacit and implicit machine knowledge, or still under the inherent human innovative thinkers.

Findings

Based on this meta-analysis of the scholarly works, models, and theoretical assessment, this work brought forward the critical necessity of Knowledge Transfer in caring forward knowledge to future successors, thereby the knowledge is encapsulated through tacit controls, implicit knowledge, and the scope of explicit knowledge. Where tacit and implicit knowledge are embedded human traits further intrinsic to their knowledge system, these are the core building blocks that bridges forward the knowledge object to the next human keeper of the knowledge. The explicit components are the documented knowledge attributes which are transferable, but one may question is that sufficient for a complete knowledge-object? The belief is that having the three components tacit, implicit, and explicit will provide completeness in ensuring knowledge and the integrity of knowledge transfer.

The notion of the traditional Knowledge Transfer construct coupled with Artificial Intelligence innovations has the potential of unforeseen consequences in the adoption of this technology. Scholarly theorists are in both camps for the greatness of advancements and the downtrodden perspective (Spiekermann, 2022). With the implementation of AI into all areas of industry, government, academia, healthcare, and military, just to highlight a few applications, the systems will change the human order of process and found knowledge in the domain. It is critical not to be paralytic in the advancement of innovation; however, it is believed that human impact on the knowledgeable objectives of current works will be disrupted, thereby the paradigm of AI integration will be yielded as a technology disruptor. This will change how things are done. For the future successors of knowledge, their predecessors will no longer bear the fruit of their knowledge, where the thread of human communication will wither and the previously understood knowledge-object will cease in humans over time. In some areas this may have minimal impact; although, as brought forth from scholarly predecessors, there may be unforeseen consequences in advancements. For these unknown consequences, it is difficult to substantiate loss of human innovation as coupled with the loss of knowledge transference, where the impact from this lens requires further study.

Hinging on the research questions: "Q1: Are humans at risk of losing the body of knowledge through the elimination of person-to-person knowledge transfer?", and "Q2: Are humans at risk of losing tacit, implicit, and explicit understanding of knowledge-objects in their domain of expertise?", further research is needed to further measure the effects of diminishing human function with AI advancements. However, considering the analysis of scholarly works, the elements of KT have been essential in the human development, and as systems further integrate into human co-virtual existence, the belief still aligns with the importance of knowledge experts embedded with the hidden tacit and implicit knowledge to still hold that understanding and progress the line forward to successors. In perspective, the machine will capture fractional attributes turning it into explicit knowledge thus becoming system knowledge; however, the inherent human nuances may be uncapturable in this modern age. Specific to humans losing control of the body of knowledge as reflected in Research Question Two. As the AI systems disengage human controls and oversight using AI adaptation, it is plausible that it will create knowledge-objects, becoming machine-only knowledge absent of humans, and without transference to humans. From this perspective, human understanding and interpretation of the machine knowledge-objects will be a non-vernacular association, and with no certainty of understanding. With the perspective of human- knowledge lagging machine-knowledge, further research is recommended to examine the divide of a foreseeable human machine gap, and to identify what is the essential human knowledge necessary for future advancement.

Conclusion

The perspective from this meta-data research concludes that humankind could be at risk of losing human skills and understanding the completeness of knowledge-objects as human works are superseded through transformation to machine systems. It is difficult to measure the significance of the skills that will be no longer needed as well as the critical knowledge that humans will need going forward for future innovation. In addition, within the human-machine divide, the advancements of machine forging knowledge through future progression with limitation excluding human knowledge transference, the impact to the overall body-of-knowledge is not yet certain. Future work is necessary to further identify the important knowledge-objectives that are needed for human advancement, or even basic human needs. Who or what determines if it is acceptable to lose inconsequential knowledge, much less determine that the knowledge itself is inconsequential? Future research is needed to align the pathways for Knowledge Transfer of the information and concepts that cannot be lost. Human history is full of examples of loss of knowledge, from the Ancient Egyptians to the previously noted Roman Empire. While the reasons for these losses vary, human-kind struggles to regain these lost pieces of knowledge for large swaths of time, if the knowledge is regained at all.

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