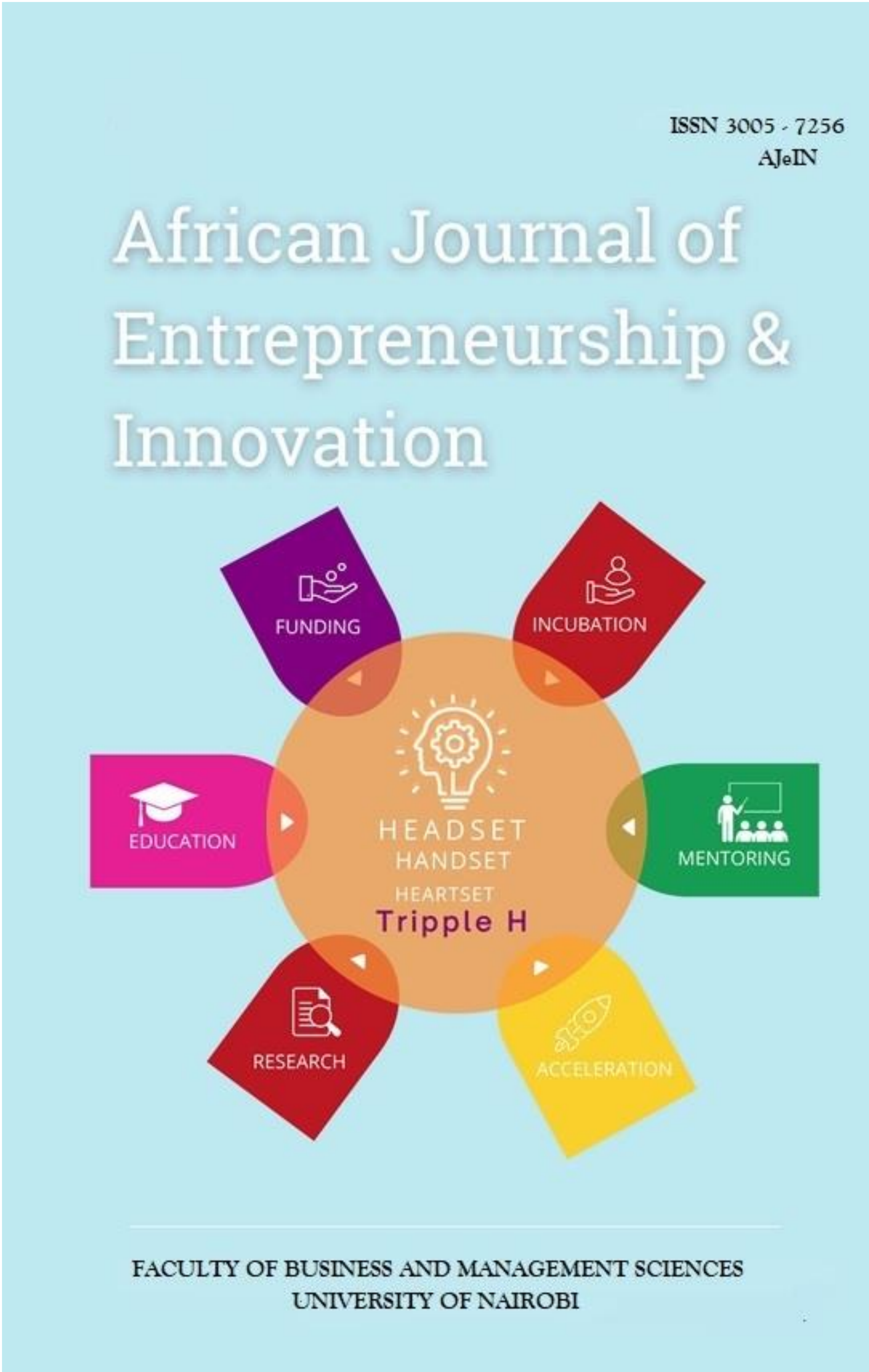
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Start-ups expert systems development capability maturity model for developing countries

By: Wangai Njoroge Mambo [1]

Abstract

There is extreme scarcity of Artificial intelligence (AI) expertise in many developing countries (DCs). Expert systems (ESs) is one class of AI systems that can solve this problem by enabling novices' and less skilled workers build their capabilities and upgrade their skills. DCs should start with small and simple ES development as required skills are available and they have fewer risks. Start-up firms are suitable for initiating creation of AI industry as they require less capital, are easier to create and run than larger firms. The ES start-up maturity model presented by study will guide setting up start-ups that build small and simple ESs then progressively in incremental steps moving to larger and more complex systems when they develop prerequisite capabilities. Design science research framework was used to create ES maturity model and descriptive evaluation to evaluate the model.

Key Words: *capabilities, expert systems maturity model, developing countries, start-ups*

Introduction

There is heightened interest in artificial intelligence (AI) in many sectors of society, industry, academia and government triggered by fascination of AI technologies like self-driving cars, generative AI and entertainment robots. It is important to diffuse AI technological and management knowledge to less informed and unaware potential adopters and software developers. For developing countries (DCs) with very few firms building AI technologies, creating start-ups that develop small and simple AI systems that meet needs of niche markets is a promising starting point.

Expert systems are used to capture human expertise in a narrow domain of knowledge and embedding expertise as executable software. The ESs have knowledge and capabilities like those of an expert in that domain, which can be utilized by all those requiring it. Economists have a long history of engaging with ESs and transformative nature of ESs requires discussion and debate on AI fueled society and many possible paths to that future (Bickley, Chan and Torgler 2022). Strategic innovation (Viliam and Michal, 2010) and technology innovation capability building ESs (Jami et al. 2019) are used in innovation field. AI systems for strategic innovation and technology capability building like ESs can save Africa from catastrophe similar to ones that resulted from missing 1st, 2nd and 3rd industrial revolutions (Mambo, 2023). Missing the 4th industrial revolution will increase gap between

[1] *Adjunct lecturer, Computing Department of United States international university, Kenya, Email: mambown@protonmail.com*

industrialized and least industrialized countries significantly that it will become improbable for them to catch-up.

There is need to create transdisciplinary education programs that combine AI and non IT disciplines for example with social sciences (Thurner and Socher, 2023). These programs create professionals capable of developing ESs in areas of their expertise. The continent's cocktail of problems can be solved by a cocktail of design thinking, problem based learning and system thinking methods to build required capabilities (Nyemba et al. 2020) which can be aided by creating ESs to support the processes.

An information systems AI systematic literature review categorized AI into eight domains; one of which was ESs (Collins et al. 2021). Most AI maturity models differ on business problem domain for example they are general, for auditing, logistics, retail, innovation management (Sadiq et al. 2021) and human centered by privileging human control and societal aspects over AI(Hartikainen, Väänänen and Olsson, 2023), but not on type of organization or AI focus. An exception is social technical maturity model focused on responsible AI and for all types' business organizations and domains (Akbarighatar, Pappas and Vassilakopoulou, 2023). Maturity models can also be differentiated according whether they are for start-ups or other types of organizations and the eight AI domains instead of business problem domain. This study's AI maturity model focuses ESs AI domain, is general on business domain and specific to start-up organization type. Design thinking and design science are used in social science. These methods were used to create some of AI maturity models presented in literature.

Connecting AI related revolutions, innovation, teaching and learning produces skilled manpower that when enabled with cognitive devices drive industry 4.0 revolution (Bullón et al. 2017). AI enabled fourth industrial revolution is likely to be followed by fifth digital ecosystems industrial revolution (Nyemba et al. 2020). The two revolutions are likely to make AI the dominant technology. An AI course on industry 4.0 revolution is being taught in a Namibia university (Shipepe et al. 2021). More AI courses focusing on industry 4.0 and Internet of Things combined with digital revolution should be introduced.

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Student interns provide affordable labor for start-ups, sometimes the only economically viable way for DCs start-ups to survive (Fagerholm et al. 2018). In many DCs it is hard to get good software engineering (SE) developers forcing startups to survive by depending on poorly paid interns (Da Silva et al. 2005).. Different DCs pay their interns differently, some better than others but most of them lower than developed countries.

This study ES maturity model is for informal and formal start-ups. An AI researcher, practitioner or lecturer developing a commercial ES using a maturity model has to consider technical, social, organizational and marketing issues which are best dealt with in formal or informal start-up organizational settings.

China has found two pathways to establish itself as global AI leader: by creating a community of practice through cooperating with other nations, universities and AI talent (Steckman, 2019). DCs can seek to be regional leaders by adapting developed countries AI technology leaders' pathways to their context. DCs universities and start-ups can align their strategies to country's national strategies and cooperate with regional universities and business organizations even those that are competitors.

The study objectives are:

a) To carry out AI maturity models literature review.
b) To design and create an ESs adoption and development capability maturity model for DCs formal and informal start-ups.

This paper is divided into six sections; the first is introduction that presents basic foundations of study and the research questions. The second section presents research methodology. The third section presents literature analysis, synthesis, the problem and suggested solution. The fourth section is creation of maturity model and fifth section evaluates the model and final section concludes research.

Methodology

The study used design science research framework (DSRF) because study involves both research and innovation (Hevner et al. 2004). Creating maturity model involves synthesizing research knowledge and innovation to create novel model relations and components. There are several DSRF's and Takeda et al. (1990) abduction, deduction and circumscription design model cast into design science research by Vaishnavi and Kuecher (2009) was selected because it is based on sound foundation of a design theory and derived from AI systems research and practice. DSRFs research methodologies are used to develop AI maturity models (Becker, Knackstedt and Pöppelbuß, 2009, Fukas, et al. 2021a, Alsheiabni, Cheung and Chris, 2019) and are a means to effectively build capabilities.

The research framework consists of five steps (Vaishnavi and Kuecher 2009):
Problem awareness – The problem of ES adoption and capability building was established by literature review.
Solution suggestion – An ES capability maturity model starting with minimum or no management and ES development capabilities and building capabilities at minimal cost is suggested.
Development – The maturity model will be developed
Evaluation – The maturity model be evaluated by showing model is appropriate for DCs context and the way start-ups are created and grown.
Conclusion –The research will be concluded.

Findings and Discussions

This section presents design science research problem awareness and solution suggestion steps.

Artificial Intelligence and Expert Systems

AI is expected to radically transform government, industry, business and disciplines. AI driven industry 4.0 revolution has brought most drastic socio-economic transformations ever faced by humankind and the next big change is smart manufacturing (Gopi and Williams, 2021), through supporting different dimensions of technology innovation capability building for example innovation evaluation for competitive advantage (Jamil et al. 2019), which can support many aspects of AIs start-up creation and growth.

Interest and investments in AI are increasing in all regions of the world. South Africa was among among five countries in the world with highest growth rate in AI hiring between 2016 to 2020 while between 2016-2019 Sub-Saharan Africa had seven-fold growth in AI peer reviewed research publications (Stanford, 2021). This trend has accelerated in 2020-2024, indicating if the trend is supported to continue the region can rapidly catch up.

Expert System Adoption and Development

Combining knowledge based systems and progressive web is a recombinant type of IT innovation for sustainable development (Fukas and Thomas, 2021b). The recombinant innovation belongs to class of systems called AI based systems that consists of AI, software engineering and other non-AI systems. AI combinatorial innovation combines existing technologies and ideas in new novel ways (Boden, 2009). ESs is one type of knowledge-based systems. DCs combinatorial innovation projects combining ESs and other computing systems can have members from different computing domains to alleviate shortage of skilled developers', build expertise and capability in participating domains. In addition to creating transdisciplinary education programs that combine AI and non IT disciplines (Thurner and Socher, 2023). The transdisciplinary majors will be enable transfer and unification of knowledge between disciplines.

AI professionals have to choose to be technology adoption leaders, followers or resistors but continuous adoption resistance will lead to their skills becoming obsolete (Gillard, Bailay and Nolan, 2008). However not every new technology is better than one it's trying to substitute (UNIDO, 2005). Not all ES innovations should be adopted or old ones discarded immediately new innovations are created.

Technology catch-up refers to a country increasing catch-up speed or skipping certain stages of technology development (Juma, and Norman, 2002). AI policies should be created to support AI research, innovation and ecosystems (Nayebare, 2019) for technology leapfrogging. Start-up ESs development accrues technical debt (TD) by trading off improving important urgent start-up survival aspects at expense of other important but less urgent aspects of start-up and ES development. Start-ups introducing TD determine the right level of good enough debt (Besker et al. 2018). AI catch-up model requires building capabilities and maximizing benefits to society, aided by governments research and development (RD) capability building policy (Galvez, Culaba, Dadios and Bandala. 2019). Most start-ups TD is acquired during development phase and paid during maintenance phase.

AI is one of most exiting innovations for simpler, more efficient production in agriculture, industry and services that can generate many jobs (Rosales et al. 2020). This can help solve problem of DCs high unemployment. AI presents opportunities for developing powerful applications using ordinary PCs and freely available software's. This makes AI software start-ups industry entry easier compared with many other advanced hardware technologies like robotics that require expensive manufacturing equipment.

Starting with simple and cheap technologies designed for a large number of potential adopters increases chances of higher adoption rates. Technology adoption starts with innovator adopters who usually have a lot of resources and like experimenting with new technologies (Rogers, 1995). Innovator adopters then act as agents to diffuse innovation information and knowledge to next group, the early adopters.

Globally AI research is dominated by developed countries as developing countries undertake other research needs and priorities that are more pressing (Atkinson and Solar, 2009). However, ignoring AI research may seem necessary for now, but in long run can have disastrous consequences, as it is likely to make these countries to lag further behind in all their research priority areas. AI in general and ES in particular can be used to automate all steps of technology innovation: basic, applied research and development (Rosales et al. 2020) and even ES innovation process. AI is most transdisciplinary discipline with respect to unifying knowledge from many disciplines. A trans-field for transdisciplinary research in SE and AI integrating society has emerged (Mambo, 2022). Society is important in establishment and growth of industry as it determines those that adopted, developed further or rejected.

One way of increasing AI adoption, creation and industry growth is developing national AI strategy (NAIS). Mauritius was first African country to develop a NAIS in the continent (Mauritius, 2018). Brazil and Chile have released their AI national frameworks; and Latin America and Caribbean countries mainstreamed innovation social impact in their AI strategies (Nettel et al. 2021). Countries with goals to prioritize ESs should mainstream ESs within national AI policies and strategies.

AI enable leap frogging some stages of technology development by leveraging knowledge and values of local people (Nayebare, 2019). DCs have leap frogged in mobile telecommunications. Telecommunications uses AI and vice versa, both are part: industry 4.0 and IoT revolutions. Training policy makers, strategy developers and AI experts together can better inform decision makers of AI capabilities and its impact (Nayebare, 2019). Transdisciplinary approaches help different disciplines collaborate with society.

A Systematic literature review found motivations to adopt AI were technology catch-up, increasing productivity, aligning with country's policies and strategies, (Kabalisa and Altmann, 2021) motivations that reinforce each other. A barefoot approach designs DCS ESs by counteracting DCs weaknesses and leverages DCs strengths (Riesco et al. 2014). The maturity model presented by study is barefoot oriented.

Cost of starting, growing and maturing software start-ups is lower than that of hardware's start-ups making s them more affordable. Every country can afford to have at least 100 AI start-ups. National strategies and policies should include start-up ecosystem maturity. DCs can ensure they have at minimum an AI software ecosystem at nascent stage. A nascent AI software ecosystem is a recognized software hub, with some start-ups, few investment deals and no great output (Cukier and Kon, 2018). The nascent ecosystem ensures countries keep a breast with AI developments, attract foreign SMEs AI investors and can quickly upgrade the ecosystem if needed.

Technology Capabilities

Technology start-ups build catch-up capabilities through acquiring knowledge, learning from doing, experimentation, researching and inventing then putting what is learnt to practice. Creating an enabling environment for AI start-ups to thrive will help avoid negative consequences of missing industry 4.0 revolution, missing the previous three industrial revolutions is cause of many problems Africa faces today (Arakpogun et al. 2021). Start-ups begin with little or no capital, limited work force and experimenting to discover how to evolve start-up and create innovations under scarce resource conditions.

Chile is a Latin America ES technology its trajectory (Atkinson and Solar, 2009):
It started with AI research goal of solving practical industry problems. Early ESs developed was for mining, process control and medicine were to meet this goal. PUC organization pioneered the first ES use in industry that lead to first ES company SOLEX in early 80's.

Factors firm size, employee's education level, product innovation, organization innovation, process innovation and business inhibitors are blended with design and organization innovation trajectories to create sustainable competitive advantage (Navas, Hwang and Yoon, 2021). Start-ups easily transform their technology and organization's architecture by experimenting with these factors.

Capability Maturity Models

AI maturity models helps an organization identify and visualize steps towards maturing capabilities (Alsheiabni, Cheung and Chris, 2019). The organization starts by determining its current capabilities, the model prescribes best practices to build capabilities to reach next level. There are few AI start-ups in many DCs and ESs start-ups are even fewer. For those with few or no start-ups more start-ups need to be created to reach a critical mass needed for formation of AI industry. Maturity models lowest level is AI ignorance and higher levels replace ignorance with knowledge, capability and awareness (Lichtenthaler, 2020) they can be designed for any organization, regions, nation or international.

Start-ups have high failure rate and AI start-ups have even higher rate. DCs start-ups failure has more negative consequences for most owner entrepreneurs have fewer alternatives for earning income compared with those in developed countries. Software start-ups embrace project failures to validate their learning to be able decide whether to pivot by changing strategy, business elements, concept and product (Bajwa, Wang, Duc, and Abrahamsson, 2017). A start-up success depends on how well it learns from failures, as failures often lead to discoveries.

AI transformative and innovative abilities powers AI capability building journey (Yams et al. 2020). Different maturity models based on different paradigms for different problem domains (Sadiq et al. 2021). For example design paradigm oriented design science maturity models (Mettler, 2011). University capabilities are more volatile than those of other organizations, because AI students after a few years graduate and leave with their capabilities.

Creating or turning some student projects into open source projects and providing incentive for students who graduate to continue participating in projects they initiated while in university. The capabilities can be built using university entrepreneurship, intellectual capital and student employability maturity models (Tocto-Cano et al. 2020). A university can turn student projects into open source projects driven by student employability maturity model making students more employable at same building university AI capabilities, IP maturity model can help create and protect open source projects intellectual capital and entrepreneurship model drives university-student start-ups formation and growth.

Maturity model design principles are oriented towards application domain, purpose of use, class of entities under investigation, differentiation from existing maturity models, design process, degree of validation and target group (Pöppelbuß and Röglinger, 2011). This study's maturity model's application domain is ESs for formal and informal start-ups, the purpose is to provide pathway to upgrade capabilities. The study's model difference with other AI maturity models with its focus on ES domain, start-ups, and applicability to any business domain.

Metrics used to measure countries AI RD capabilities are number of journal and conference publications, AI capabilities, skills, hiring, investment, number of funded start-ups, patent number and citations (Stanford, nd). These metrics can be used by countries to measure their national AI capabilities. Computing schools of DC Universities that aim to become AI technology leaders should increase their publications in AI international journals but should operate at least one AI journal and make significant AI contributions to relevant university conferences to promote AI research specific to their countries. Start-ups can include relevant metrics in their strategies. Two other start-ups success factors are strategies for dealing with AI barriers and drivers. Barriers and drivers sometimes reinforce or counteract each other for example the barrier lack of AI strategy can create another barrier lack of AI talent in the organization and the driver decision making ability can lead to creating a sustainable process driver (Kar, Kar, and Gupta, 2021). Start-ups aware of barriers and drivers are better able to navigate technology landscape. Maturity models could be designed to deal with barriers for example lack of AI talent that can be overcome by developing human resource management and innovation capabilities that enable generation innovative ideas and products (Arakpogun et al. 2021). Maturity models have to be designed to deal both enablers and inhibitors.

Lagging behind DCs can start with increasing number of people trained in AI and ensuring AI students get industrial attachment to gain skills. Government must drive this process initially and can have at least a department or center focusing on AI. United Arab Emirates takes this to a higher level by having ministry of AI. Intelligent tutoring including tutoring ESs will increasingly support online courses. AI can be argued to be secret sauce that enabled increasing massive online courses (MOOC) student numbers to tens of thousands (Stanford, 2016). Teaching AI introductory courses to all science, engineering, computing students using MOOC supported by AI lowers costs compared to physical teaching.

Problem Awareness and Suggested Solution

Sub-Saharan Africa and some other developing regions of the world face severe skills shortage that can be overcome by using ESs. For example an ES has solved university skills shortage caused by brain drain through immigration of lecturers (Sakala et al. 2010). The problem is how to upgrade their capabilities and grow them systematically by learning from doing and learning by experimenting.

Suggested solution is to enable more individuals to develop ESs to build technical capabilities, create and grow start-ups capabilities. Start-ups lack of resources requires prioritizing building topmost ranked skills by having learning agility and being able to jump easily between different SD problems (Mangiza and Brown, 2020), which can be learned from other successful start-ups experiences.

Expert System Catch-Up Maturity Model

This section is for research development step, a maturity model is developed using design science research framework shown in table 1. Rapid evolution of AI, ES and limited resources necessitate DCs start-ups tactics, strategies and capabilities to evolve continuously based on cumulative synthesis of lessons learned from experience, practice and research.

Table1. Expert System Capability Maturity Model.

Level ES Features, employee skills and start-up growth

Level 0 - Ignorance Start-up lacks awareness of usefulness, importance of building ESs capabilities and growing start-up systematically. The start-up runs on initial capital raised and possibly non AI Information technology income generating activities. Initially startup owner/s may work on startup job and some an extra one to help support startup

Level 1 - Basic understanding and skills. Start-up has basic awareness of usefulness, importance of building ESs capabilities and growing start-up systematically. Employees practice developing simple ESs to learn and build basic capabilities. Start-up generates income to support itself from non AI Information technology activities. Sales from ESs are negligible. Startup owner/s may continue working two jobs.

Level 2 - Intermediate knowledge and skills. Start-up creates intermediate knowledge, skills and capabilities through learning by doing and experimenting acquired by startup management and building simple ESs. Startup learns by adopting and using simple open source ESs and shells. Open source ES software is free and provides source code enabling developers to more easily build capabilities at lower cost. It builds ability to develop simple small knowledge based systems used by businesses with many software engineering (SE) modules and one or few small simple ESs modules. It learns from software start-up patterns and methods (Cukier and Kon, 2015). For example entrepreneurship and innovation methods and fragments like lean start-up methodology fragments (Ries, 2011) to distil best practices. It develops simple commercial hybrid SE ES systems. Start-up generates income by open source support activities selling their hybrid ES systems and imported large ESs. Start-up owner/s stop working external jobs and focus only on start-up.

Level 3 - Basic Experimenting. Start-up start experimenting with developing simple small commercial ESs based on idea small is better to begin with. ESs develop at this level differ from level 2 by having no conventional SE components. It incrementally adopts entrepreneurship and innovation methods and techniques: starting by adopting their simplest parts then incrementally adopting more complex parts until they are able to use complete methods like lean start-up methodology. Networking with other start-ups in neighborhood and beyond to learn, share knowledge, solutions and experiences. They allow technical debt whenever it's necessary for start-up survival. Start-up moves away from non ES IT activities. It continues selling imported ES large systems. Start-up starts automating its internal activities with ESs.

Level 4 -intermediate Experimenting Start-up experiments gradually with developing increasingly larger ESs. Every project must have a clear goal and vision to build capabilities. Start-up creates experimental ESs never to be used in practice. Start-up must ensure commercial ESs are used by at least one individual or organization even if it means giving them for free as shareware or open source. Although given for free but evidence generated that it works in industry helps start-up builds valuable credibility to use for marketing. Start-ups from level 4 and higher generate income only by selling ESs they have developed, imported ESs and related activities.

Level 5 – Partnering and forming alliances Start-up starts form partnerships and alliances with other AI developing firms whether large or small, local or international. Forming these relationships should start by start-ups alliances and partnerships as they are easier and faster to form and manage. Start-up use approaches like open innovation maturity model based on partnering (Enkel, Bell and Hogenkamp, 2011) and sixth generation RD where organizations carry out basic and applied research together as a consortium but research commercialization is left open for participating organizations do it alone or in sub groups (Nobelius, 2004). Start-up down scales approaches for medium and large enterprises to make them lightweight. Win-win alliances focused on building relationship capabilities by acquiring knowledge and ESs together (Matusik and Heeley, 2005). If there are no start-up groups to partner with, start-up advocates for institutional and government support in creating AI ecosystem.

Level 6 - Research and Development. Start-ups incrementally perform ES innovation research and development. The goal is not to develop radical innovation capabilities but to build ability to develop incremental capability to be able to learn from RD done by AI technological leaders. The highest level innovation capabilities start-ups are likely to develop are technology breakthrough that uses significantly different technologies that provide similar benefits to existing technologies rather than radical innovations that use new novel technologies, create new markets that have higher benefits (Queiroz et al. 2020). Start-up teams consist of ES developers from different disciplines and knowledge experts from different problem domains. Start-up has advanced knowledge and skills of managing the start-up. The start-up uses RD knowledge in its catch-up strategy to become a regional leader or global fast follower. Alliances and partnerships upscale partnering capacity (Enkel, Bell and Hogenkamp, 2011). Start-up partnerships and alliances could approach larger firms that have carried applied ES research or have patented, which larger firms are not interested in commercializing. Start-up strength in numbers increases chances of attracting attention of larger firms.

Level 7 - Continuous improvement. Start-up continuous improves ES development and start-up management by upgrading knowledge, capabilities and skills. Start-ups have proactive alliance and partnership selection strategy and share partnering expertise with collaborators (Enkel, Bell and Hogenkamp, 2011). The startup uses state of art methods and technologies in developing ESs.

Few organizations reach highest capability level of most maturity models. It takes over three years for an individual novice to become an expert. It will take a start-up a minimum of five years to build capabilities from level 0 to reach capability level 4. The maturity model provides opportunity for advanced start-ups and larger firms with capital to create ES start-up innovation hubs in DCs.

Maturity Model Evaluation

This section is DRSF evaluation step. The ES model was validated by descriptive evaluation through comparing it with other AI maturity models. Industry model evaluation is another approach that is not often used because it requires five or more years to do so (Esterhuizen, Schutte and Du Toit, 2012). Industry evaluation can be done after with descriptive evaluation. AI maturity models are also developed in two phases: phase one doing research and publishing journal article and phase two implements the model and evaluates it (Hartikainen, Väänänen and Olsson, 2023). Design research artifacts can be evaluated by comparing them with similar artifacts (Baskerville et al. 2009). Existing AI maturity models were not evaluated with industry evaluation.

Descriptive evaluation uses relevant research to build a convincing artifacts utility argument (Hevner et al. 2004). DCs that face severe resource scarcity when building ESs have to do so with few resources available, negligible capital through discovery by experimentation, learning from similar successful innovations and entrepreneurship cases. Textile firms increase productivity and lower costs through applying ESs and experimentation to learn from their manufacturing activities (Bullón et al. 2017). A start-up software pattern is solution to commonly recurring problem, an example pattern is learning from entrepreneurship and innovation methods (Cukier and Kon, 2015). Methods are based on industry best practices.

Majority of DCs AI start-ups are likely to be started by IT graduate students who are unemployed or under employed who can reduce capital required to get started by for example by operating from their homes or garages with old PCs even ones students used in their studies, using open source platforms and programming languages that are free. They can learn and practice to build maturity basic level 1 capability by learning to develop simple ESs, if they did not do so during their studies and maturity Level 2 intermediate capability by acquiring, adopting open source ESs and learning from innovation and entrepreneurship methods. The study's ES maturity model is based on increasing learning and experimentation similar to lean start-up methodology for start-ups (Ries, 2011). Two open source systems: JavaDON ES shell written in java programming language (Tomic, Jovanovic and Devedzic, 2006) and JESS ES for acquiring knowledge for software design and development implementable as an Applet (Annaiahshetty and Prasad, 2013) could be used. A start-up entrepreneur may decide to create and use an ES to support software design and development, and provide it as shareware to another firm to produce evidence to use in marketing it. Several open source ES systems, shells exist and publications are available. Start-ups can build capabilities by experimenting with open source shells and frameworks in level 3, intermediate experimenting level 4, and RD level 6.

DSRF artifacts are evaluated by researcher reasoning about their purpose, internal structure and conditions under which artifact is expected to work and others will not (Sonnenberg and vom Brocke, 2012). Compared with AI maturity models (Sadiq et al. 2021, Alsheiabni, Cheung and Chris, 2019, Cukier and Kon, 2018, Pöppelbuß and Röglinger, 2011): study's ES maturity model levels 1, 2 and 3 are simpler than equivalent levels of these models, can be implemented by a single start-up employee and mirrors the way software development capabilities are developed by computing students and new employees.

Conclusion

This section is design science research conclusion step that summarizing study. ESs can assist novices and less skilled workers do work requiring higher skills than ones they possess. Being able to develop ESs can help DCs fill skill gaps in different areas. The ES capability maturity model can aid building ES development, start-up creation and growth capabilities in low cost way.

The model can be used by unemployed students and people who have basic AI knowledge and skills to build startup management and technical capabilities. The model is based on self-bootstrapping using what is available to create what is needed. The ideal solution of having all required prerequisites is not feasible in many cases in DCs. Creating alliances and partnerships between less advanced startups between themselves and across with more advanced local and international start-ups and larger firms is important step towards maturing capabilities.

The study's ES model was evaluated it by descriptive evaluation by argument that showed model meets requirements from maturity model literature and compares favorably with other AI maturity models used in industry. Industry evaluation is left as future work.

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